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Improved Artificial Neural Network with High Precision for Predicting Burnout among Managers and Employees of Start-Ups during COVID-19 Pandemic

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Abstract: Notwithstanding the impact that the Coronavirus pandemic has had on the physical and psychological wellness of people, it has also caused a change in the psychological conditions of many employees, particularly among organizations and privately owned businesses, which confronted numerous limitations because of the unique states of the pandemic. Accordingly, the current review expected to implement an RBF neural network to dissect the connection between demographic variables, resilience, Coronavirus, and burnout in start-ups. The examination technique was quantitative. The statistical populace of the review is directors and representatives of start-ups. In view of the statistical sample size of the limitless community, 384 of them were investigated. For information gathering, standard polls incorporating MBI-GS and BRCS and specialist-made surveys of pressure brought about by Coronavirus were utilized. The validity of the polls was affirmed by a board of specialists and their reliability was affirmed by Cronbach's alpha coefficient. The designed network structure had ten neurons in the input layer, forty neurons in the hidden layer, and one neuron in the output layer. The amount of training and test data were 70% and 30%, respectively. The output of the neural network and the collected results were compared with each other, and the designed network was able to classify all the data correctly. Using the method presented in this research can greatly help the sustainability of companies.

Keywords: burnout; artificial intelligence; RBF neural network; COVID-19; resilience; mathematical techniques

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1. Introduction

The World Health Organization distinguished Coronavirus as a broad pandemic on 11 March 2020, when diseases and deaths expanded dramatically. The principal case was accounted for in Wuhan, China [1]. As per insights gained, from the start of this pandemic until 30 September 2021, 233,136,147 cases have been contaminated around the world, of which 4,771,408 have died [2]. Be that as it may, Coronavirus is not simply a significant well-being emergency, but rather the infection is changing the construction of worldwide requests in business and the economy [3]. Such pandemics, in addition to influencing the actual strength of people, will likewise affect emotional wellness [4]. As such, Coronavirus has influenced the personal satisfaction of numerous residents, and according to the demographic and social characteristics, the experience of the COVID-19 disease was different from one person to another [5]. During the pandemic, quarantine regulations expected residents to decrease social collaborations to lessen the gamble of new contaminations [6]. Work terminations, amusement terminations, expanded working hours in emergency clinics and clinical focuses, and travel boycotts were among the limitations that were upheld in numerous nations. These conventions and limitations, alongside the feelings of dread and tension of people and families contracting Coronavirus, diminished correspondence and collaboration and thus decreased business pay, prompting nervousness and mental pain for some individuals [7]. In such a manner, one of the significant results of ongoing pressure brought about by Coronavirus is burnout; burnout is a mental disorder that occurs as a result of persistent occupation-related pressure and is described by word-related upsetting encounters, expanded responsibility, diminished work quality, and social disengagement [8]. In this situation, employment loses its significance and importance for the individual. An individual who has experienced burnout feels constantly depleted and tired, has a forceful state of mind, is fairly cynical and dubious in relational connections, and will be, for the most part, negative [9]. In this way, on the grounds that the idea of certain emergencies and encounters is to such an extent that individuals definitely experience the ill effects of emotional wellness issues, individual and intellectual abilities with the assistance of which individuals can oppose in emergency circumstances have been viewed as sure by clinicians [10]. Clinicians accept that there are direct elements between distressing occasions and mental problems that make upsetting occasions distinctively affect people [11]. Subsequently, scientists have tried to build up factors inside people that increase their level of adaptation and health [12]. One of these altering character attributes is resilience. Resilience is quite possibly the main human capacity that makes viable the transformation of basic and upsetting variables in distressing circumstances. Subsequently, resilience is perceived as a figure of fruitful transformation to change and the capacity to endure misfortune [13]. Resilience alludes to the capacity of an individual to adjust, notwithstanding encounters and emergencies, to survive, and even to be reinforced by those encounters [14].

In the meantime, as per the measurements of the World Health Organization, the number of patients with Coronavirus as of 30 September 2021 was 5,587,040, of which 120,428 had died [15]. Given the previous limitations and terminations of numerous organizations to control Coronavirus, including start-ups, burnout for directors and their representatives is unavoidable on the grounds that a significant number of these organizations had to lessen their labor force, decrease their actions, and subsequently diminish deals and income, and some of the time shut down. These organizations, in contrast to huge organizations, because of restricted assets and start-ups, cannot get by in states of precariousness for an extended period and have many difficulties. As Coronavirus is almost two years of age, it has prompted limitations for them. Hence, taking into account that there is no quick answer to lessen the pressure and burnout of directors and representatives of these start-ups, the consistent tension has caused drawn-out unsafe circumstances for start-ups that require serious consideration. Accordingly, the principal reason for this study was to research the elements of burnout in the Coronavirus pandemic and assess the connection between them with demographic variables and resilience among supervisors and workers of start-ups.

2. Research Literature

2.1. Burnout

A person's place of residence includes various factors including physical, psychological, and social factors, each of which has an impact on human health. Every person spends a large part of his life at work [16]. The signs, causes, and effects of job burnout are important topics that have attracted the attention of industrial psychologists for several years. Physical and mental fatigue caused by pressure in the workplace and self-employment, as well as signs and states of exhaustion, frustration, isolation, and despair, are called burnout [17]. This issue has had a negative impact on employees, organizations, and businesses [18]. Job burnout is caused by many things, such as the weakness or incapacity of employees, or it is related to the workplace and the mismatch between the individual characteristics of people and the nature of their jobs [19]. In another definition, the mismatch between the employee and her workplace is called job burnout, and if it grows gradually, it leads to the use of inappropriate and ineffective coping strategies to protect oneself from work-related stress [20].

2.2. Resilience

In various scientific fields such as crisis management [21], medicine [22], supply chains [23,24], or cooperation networks [25], the concept of resilience has been investigated and studied, but currently, a special concept has not been considered for it. The concept of resilience is defined by Francis and Bekra (2014) as the system's ability to reduce the likelihood of a shock, employ shock absorption if it occurs, and recover quickly after a shock [26]. Newman (2005) has introduced resilience as the ability to cope with problems [27]. The methods that are used to manage stress are efficient methods that are based on the characteristics of resilience [28]. The study and discovery of individual abilities and individual insights, which is the definition of resilience, has recently received much attention. Resilience causes progress and resistance in difficult situations [29].

2.3. Research Objectives

1. The relationship between resilience and job burnout of managers and employees of startups is investigated.
2. The relationship between the stress of COVID-19 and the resilience of managers and employees of startups is investigated.
3. The relationship between the stress of COVID-19 and the burnout of managers and employees of startups is investigated.
4. The relationship between demographic variables and the concept of resilience and job burnout and stress caused by COVID-19 among managers and employees of startups is investigated.
5. The design of the artificial neural network has 10 input variables, which include five demographic variables including age, gender, marital status, work experience, and children, stress caused by COVID-19, exhaustion, cynicism, professional efficiency, and resilience, and its output variable is Job burnout.

3. Materials and Methods

3.1. Design and Procedure

The current survey is applied for the aforementioned reasons and has a quantitative-cross-sectional methodology. The review populace was the chiefs and representatives of start-ups. As per the convention for assessing the sample size for a limitless measurable populace, 384 individuals were chosen as the factual example. Tests were gathered between early August 2021 and late September 2021. The data used in this research were extracted from previous research [30].

3.2. Instruments

In this research, a form was used to collect data.

Maslach Burnout Inventory-general survey (MBI-GS) [31]: The form used in the research [30] consists of three parts, which are exhaustion, professional efficiency, and cynicism. Exhaustion has 6 items (1, 2, 3, 4, and 6), professional efficiency includes 6 items (5, 7, 10, 11, 12, and 16), and cynicism consists of 5 items (8, 9, 13, 14, and 15). Signs of burnout are high cynicism, low professional efficiency, and high exhaustion. The six-point Likert scale was as follows: 0 for never, the first item for several times a year or less than that, the second item for once a month or less, the third for several times a month, the fourth for once a week, the fifth for several times a week, and the sixth for per day. Because in previous research [30], the standard form was used, its validity and reliability were confirmed. Based on Maslach and Jackson (1981), the 22-item instrument has a Cronbach's alpha of 0.9 for the exhaustion dimension, 0.79 for the cynicism dimension, and 0.71 for the professional efficiency dimension, and lastly, according to Cronbach's alpha, 0.76 was obtained for all items. In addition, in previous research [30], the opinions of the panel of experts were used to confirm the validity and a pilot test was used for final confirmation, and Cronbach's alpha was calculated as 0.82.

Brief Resilience Coping Scale (BRCS) [27]: This form had 4 sections on a Likert scale from 1 to 5. Based on this, score 1 shows that "this item does not describe me at all" and score 5 shows that "this item describes me completely". In this form, a score of 17 or above indicates higher resilience flexibility [30]. Because of its standardization [32], this form had validity and reliability and Cronbach's alpha is 0.86; in the present research, a panel of experts was used to confirm the validity and a pilot test was used for final confirmation of Cronbach's alpha, which was calculated as 0.83.

Researcher-made questionnaire for assessing stress of COVID-19: This form contains questions related to demographic variables, such as age, gender, marital status, employment history, and children's status, and six questions to assess the stress of COVID-19. This form has been confirmed by a panel of experts in terms of validity, and Cronbach's alpha of 0.79 has been obtained, which shows that this form is valid and reliable [30]. All the forms were completed online. Managers and employees of start-ups were asked to participate in this research after approving the research protocol. It should be added that the information provided in this research was completely confidential.

3.3. Participants

In Table 1, the tested statistical samples are explained in terms of demographic characteristics. Based on this, 167 of the statistical samples in this research [30] (43.5%) were women and 217 of them (56.5%) were men. Moreover, the average working history of women was 11.86 years, and this figure for men was 14.63 years. Out of the total number of women investigated, 133 women were married and 34 of them were single, and regarding men, 131 were married and 86 were single men. From the available statistical sample, 100 women had children, as did 118 men.

Table 1. A summary of the demographic characteristics of the statistical sample [30].

Gender	Number (Person)	Average Age (Years)	Average Job Experience (Years)	Marital Status (Person)		Children Status (Person)	
				Married	Single	Presence of Child	No Child
Woman	167	40.43	11.86	133	34	100	67
Man	217	42.84	14.63	131	86	118	99
Total	**384**	**41.64**	**13.25**	**264**	**120**	**218**	**166**

To reach our research goals, the following results were obtained.

Job burnout had a direct and meaningful relationship with burnout (rp = 0.594, $p < 0.001$) and cynicism (rp = 0.467, $p < 0.001$), as shown by the result of Pearson's correlation analysis, but its relationship with professional efficiency was negative and significant (rp = -0.322, $p < 0.01$). In addition, according to these results, there was a negative and significant relationship between job burnout and resilience (rp = -0.222, $p < 0.01$), that is, the more resilience increases, the lower the level of job burnout [30].

According to the results of inferential statistics, the stress level of COVID-19 in men was equal to 6.24, and in women, it was equal to 8, which shows that the level of stress caused by COVID-19 was lower in men than in women. It should also be mentioned that this stress was 8.94 in married women who have children and 7.97 in married men.

There was a significant and inverse relationship between the stress of COVID-19 and resilience in the sense that as the amount of stress caused by COVID-19 increases, the level of resilience decreases (rp = -0.306, $p < 0.01$). These were obtained based on Pearson's analysis.

Based on the analysis and statistics carried out [30], the relationship between the stress of COVID-19 and job burnout has a direct and significant relationship, which means that as the stress of COVID-19 increases, job burnout also increases in parallel (rp = 0.499, $p < 0.001$). Moreover, the relationship between the stress caused by COVID-19 and burnout (rp = 0.532, $p < 0.001$) and professional efficiency had an inverse and significant relationship (rp = −0.200, $p < 0.01$), and it also had a direct and significant relationship with cynicism (rp = 0.427, $p < 0.001$).

The average resilience of women was equal to 11.86 and this amount for men was equal to 13.73. These figures are according to the results obtained from the resilience of managers and startup employees [30]. In addition, the resilience of married women who had children, married men with children, single women, and single men was equal to 44.9, 10.06, 15.76, and 17.77, respectively. According to the standard of resilience questionnaire, in which a score of 13 or less indicates a lower rate of resilience, it can be concluded that the level of resilience of married people is lower than the resilience of single people. According to the results of the above research, almost 50% of the statistical population, that is, 194 people, had low resilience. Approximately 15% of the statistical population, which includes 56 people, had moderate resilience and 134 people (approximately 35%) had high resilience.

According to the statistical results obtained from the statistical population consisting of 384 people, 61 percent of them, i.e., 232 people, suffer from burnout syndrome, which includes a high level of pessimism and high exhaustion as well as low professional efficiency. Of the total number of people mentioned, the gender of 117 were men and 115 persons were women. Moreover, it can be seen that burnout among the 221 mentioned people, which includes married men and women, was more than among single women and men. Finally, from the results obtained, it can be seen that the average score of the burnout variable was 3.99, the average score of the professional efficiency variable was 2.97, and the average score of the cynicism variable was 3.72, which is lower than the professional efficiency variable. It should be mentioned that one of the ways to calculate the average scores was the Likert scale.

In this part, the first four goals of the study were explained, and the existence of a relationship between demographic variables, dimensions of job burnout, resilience, and the stress of COVID-19 was described using descriptive and inferential statistics. Next, the relationship between the input and output is determined using the RBF neural network.

4. RBF Neural Network

In this research, SPSS software was used for descriptive statistics and inferential statistics. MATLAB software is used to design an RBF neural network. In this study, 10 characteristics have been used as input for the neural network to determine the presence or absence of job burnout. Numbers 1 and 2 indicate the presence or absence of job burnout, respectively. The input characteristics include three nominal variables, namely gender, marital status, and having children, and seven qualitative variables, namely age, job experience, the stress of COVID-19, exhaustion, cynicism, professional efficiency, and resilience.

There are many analytical methods for approximating complex and non-linear functions, among which the artificial neural network is known as a reliable, intelligent, and accurate tool. In various fields of science, including engineering, medicine, and experimental sciences, neural networks are used for modeling, prediction, classification, pattern recognition, etc. [33–51]. One of the most famous and widely used neural networks is the radial basis function (RBF) neural network.

There are millions of computing units called neurons in the human brain that are connected to each other. Neurons receive information from other neurons through input pathways called dendrites. The center of neurons is called the nucleus, which is responsible for calculations on inputs. The output cable of the neuron is called the axon, which transmits information from the nucleus to other neurons. The described process is in the physiological and biochemical world of the human brain. The implementation of this process in the world of mathematics has given birth to the science of artificial neural networks. Several methods have been introduced to describe this function in the world of mathematics, one of the most famous and widely used of which is the RBF neural network. The radial basis function is the activation function of this type of artificial neural network. This neural network consists of three layers, the input layer, the hidden layer, and the output layer.

The input layer is a linear layer that collects the input characteristics of the network. All calculations and the transfer of input to output space are performed in the nonlinear hidden layer, which is activated with a Gaussian function. The output layer is a linear layer that is used to provide the output of the system. Due to the high speed of learning the RBF neural network, this type of network is very useful for real-time applications. The radial basis function in the hidden layer is defined as follows:

$$\varphi(r) = \exp\left[-\frac{r^2}{2\sigma^2}\right] \tag{1}$$

The parameter of r in an RBF is the numerical value of the interval from the center of the cluster. In the second layer, there are computing units called nodes. Hidden nodes have a center c, which is a parametric vector of a similar length to the input vector x. Equation (2) expresses the Euclidean distance between c and x.

$$r_j = \sqrt{\sum_{i=1}^{n}\left(x_i - w_{ij}\right)^2} \tag{2}$$

The output of the jth neuron in the hidden layer is shown in Equation (3).

$$\varnothing_j = \exp\left[-\frac{\sum_{i=1}^{n}\left(x_i - w_{ij}\right)^2}{2\sigma^2}\right] \tag{3}$$

The RBF network is a progressive and supervised network, for which two stages of training and testing must be completed for its implementation. In the training phase, approximately 70% of the data are randomly selected and used to fit the data. In this stage, the structure of the neural network is formed. In the end, to ensure the correct functioning of the implemented neural network, the remaining 30% of the data are applied to the input of the network to evaluate the performance of the network against the data that it has not seen until then. The correct response of the neural network to these two datasets guarantees the correct functioning of the network in operational conditions.

The implemented RBF neural network is shown in Figure 1. Table 2 shows the characteristics of the designed network. Different neural networks with varying numbers of neurons in the hidden layer were developed to find one that could categorize burnout cases with the highest rate of accuracy. This network has 10 neurons in the input layer, collected parameters, 40 neurons in the hidden layer, and 1 neuron that predicts the presence or absence of burnout in the output layer. The RBF neural network employed in this study was developed in MATLAB 2018b. All of the stages involved in training and testing the neural networks have been meticulously coded in this study rather than using pre-designed toolboxes. Several neural network construction toolboxes are included in this MATLAB package. It is worth noting that the "newrb" function was used to train the neural network. In the output layer, the existence of job burnout and the absence of job burnout are indicated by numbers 1 and 2, respectively. It should be noted that a boundary between these two classes is considered so that the data that are smaller than or equal to 1.5 are considered number 1 and the outputs that are greater than 1.5 are considered class 2. The designed neural network was able to classify all outputs correctly. A confusion matrix can be used to show the accuracy of classifier neural networks. In this matrix, the number of correct and incorrect answers for each class is displayed separately. The confusion matrix is used to show the performance of the designed network for training (Figure 2) and test data (Figure 3).

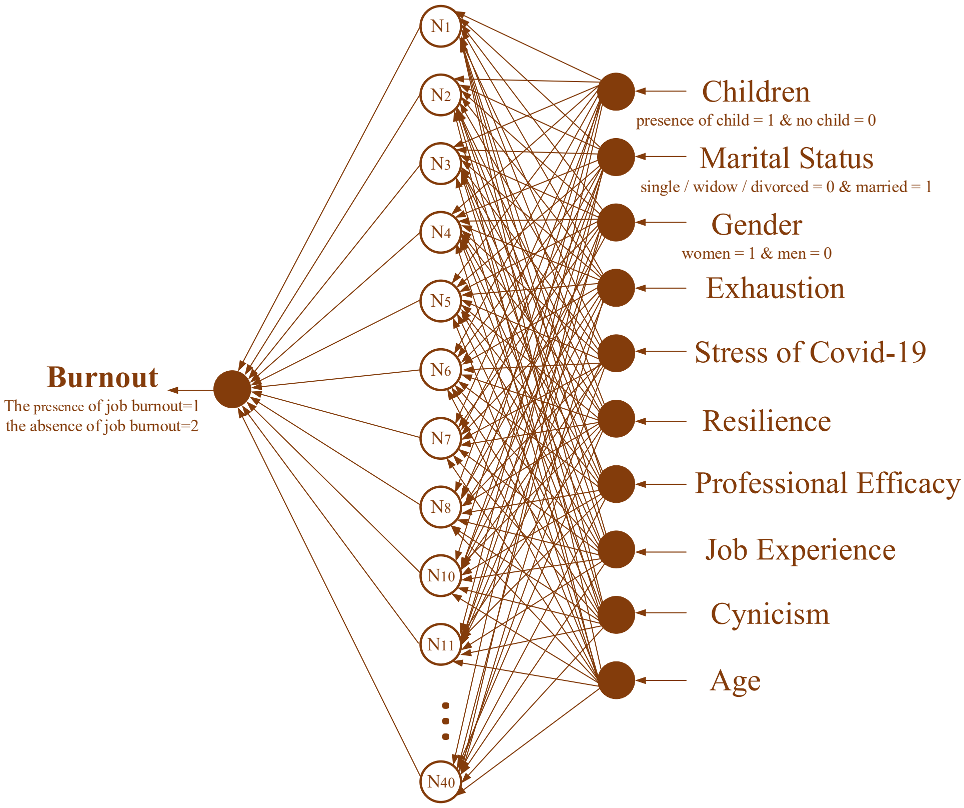

Figure 1. The structure of the trained RBF neural network.

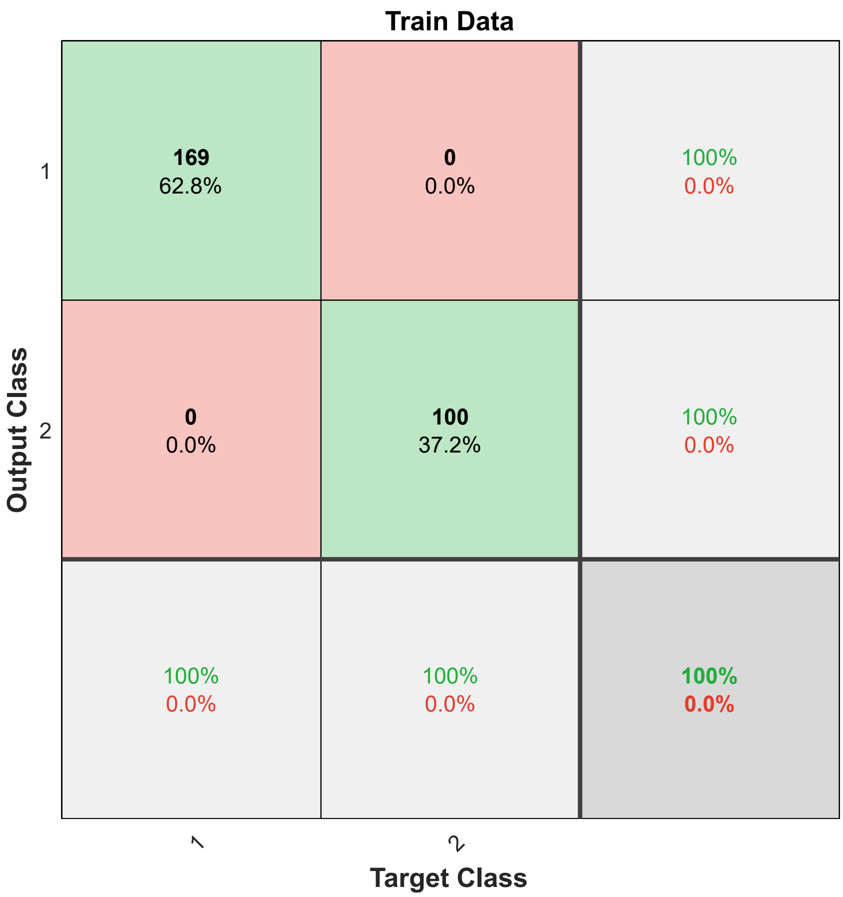

Figure 2. Confusion matrix for training data.

Table 2. Specifications of designed networks.

Output	Burnout (Presence of Job Burnout = 1 and Absence of Job Burnout = 2)	
Goal of MSE	0	
RBF spread	3	
Number of neuron in input layer	10	
Number of neuron in hidden layer	40	
Number of neuron in output layer	1	
Accuracy in classification	Train data	Test data
	100%	100%

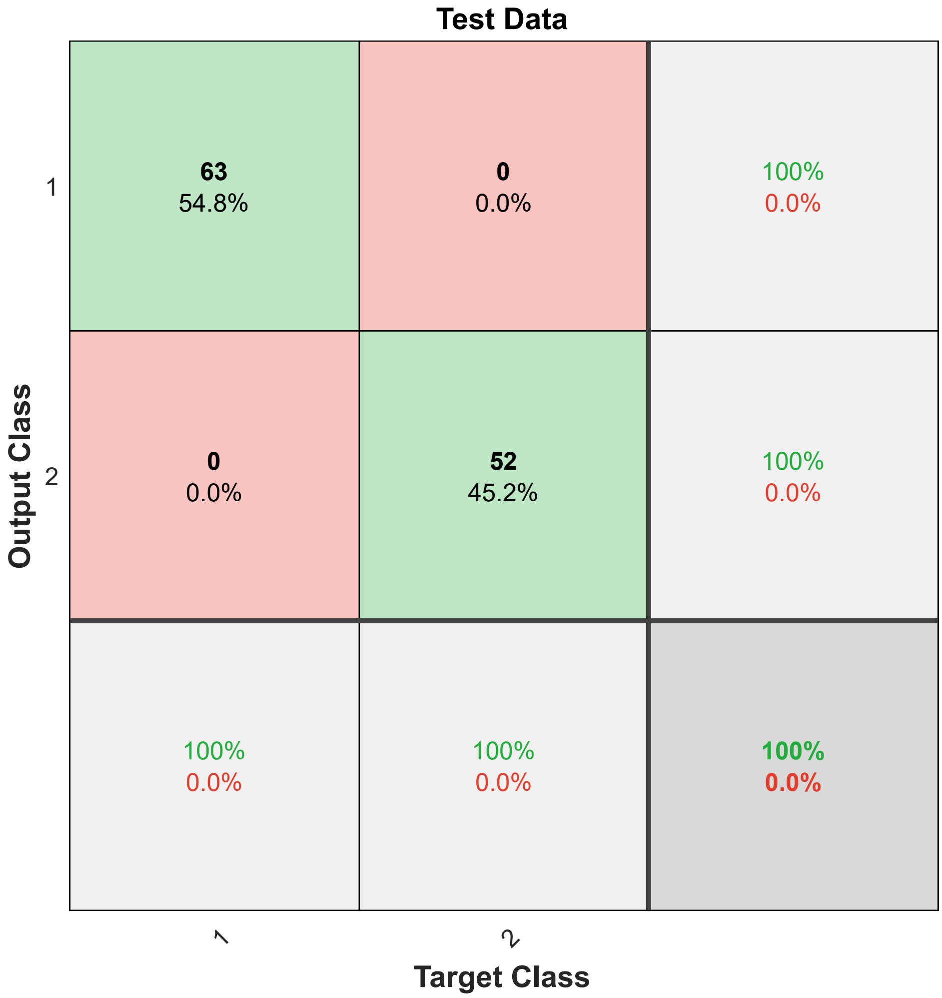

Figure 3. Confusion matrix for data.

5. Results

Investigating the relationship between demographic variables, resilience, COVID-19, and job burnout with the approach of an artificial neural network design in start-up companies was the main goal of this research. Investigating the effects of the stress of COVID-19 on the state and performance of businesses and the mental health of managers and employees is very beneficial. Based on the results, 65% of the statistical sample had medium and low resilience levels (16 and below); in addition, 61% of the statistical sample had burnout. The resilience of men is more than that of women. On the other hand, the COVID-19 stress level of men is less than that of women, and the highest level (8.94) belongs to married women with children. Pearson's correlation analysis states that the relationship between the stress of COVID-19 and resilience is an inverse and significant relationship and has a direct and significant relationship with burnout. In addition, resilience and burnout have a negative and significant relationship. Moreover, according to the analysis of neural networks, people with older age and more work experience who are married and have children have more job burnout. Furthermore, this situation is more obvious among women than men. Therefore, through this highly accurate network, information on 10 variables including age, gender, marital status, job experience and children, COVID-19 stress, exhaustion, professional efficiency, cynicism, and resilience, and the state of job burnout have been explained and predicted. The present study is innovative in terms of the subject and methodology, and its results can be used by researchers and experts in fields such as business, entrepreneurship, organizational behavior, engineering sciences, and sustainability issues. In research related to social sciences and humanities, engineering methods such as neural network design have been used less. The use of different feature selection methods, including methods based on optimization algorithms such as PSO, genetic algorithm, etc., to select appropriate features and reduce the computational load applied to the system may be an attractive topic for researchers in this field. Self-organizing neural networks such as GMDH can also be used to automatically select appropriate inputs.

6. Conclusions

In this paper, a novel numerical model in view of the RBF neural network was introduced to foresee the presence of burnout. The necessary information was accumulated utilizing surveys and was partitioned into two sections: 70% as training information and 30% as testing information. The best ANN design with the fewest mistakes was tracked down utilizing experimentation. The introduced model has 10 input characteristics, 1 output and 1 hidden layer, and 40 neurons. Age, job experience, the stress of the disease of COVID-19, exhaustion, cynicism, professional efficiency, resilience gender, marital status, and having children were considered input characteristics and burnout was thought of as the output. All samples fed to the designed neural network were correctly classified. The accuracy and remedy of the introduced model were affirmed by the acquired outcomes.

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