Predicting Intensive Care Unit (ICU) Requirement in COVID-19 With Artificial Neural Network

Yeliz Çotoy, Elif Doğu and Y. Esra Albayrak

June 7, 2021

Predicting Intensive Care Unit (ICU) Requirement in COVID-19 With Artificial Neural Network

Yeliz Çotoy[1], Elif Doğu[2] and Y. Esra Albayrak[3]

[1]Galatasaray University/ Industrial Engineering, İstanbul, Turkey
ycotoy@dogus.edu.tr,Yeliz.Cotoy@ogr.gsu.edu.tr
[2]Galatasaray University/ Industrial Engineering, İstanbul, Turkey
edogu@gsu.edu.tr
[3]Galatasaray University/ Industrial Engineering, İstanbul, Turkey
ealbayrak@gsu.edu.tr

KEYWORDS - COVID-19, Prescriptive analytics, machine learning, risk factors, Artificial Neural Network

ABSTRACT

Due to the fact that the first pneumonia case caused by the new 2019 coronavirus (COVID -19) was found in Wuhan, the impact and consequences of this epidemic, which has affected the whole world, are still ongoing. The health sector is one of the most affected sectors by this epidemic. Since the disease was new at the beginning and the treatment was naturally found later, the course of the disease has been fluctuating and is still not over. One of the greatest difficulties experienced by the health sector was the increase in hospital admissions due to the spread of the disease. How can we better manage the difficulties experienced in hospital capacities in such situations and how can we plan more efficiently has been the main question that this thesis explores and tries to find.

To this end, studies on patients with COVID-19 disease were reviewed in the literature. The common characteristics of COVID-19 patients were clarified. Demographics, symptoms of coronavirus disease 2019, laboratory evaluations, and clinical management were summarized. No geographical or other limitations were found in this study. The risk factors included in the literature are divided into four main sections. These sections are demographic, comorbidities, geographic and lifestyle factors.

In this study, it was predicted with 80% accuracy whether a person would be admitted to the Intensive Care Unit, according to the characteristics of the artificial neural network method. Prescriptive analytics and methods are included. However, if prescriptive analytics are used to make predictions in addition to statistical analysis, a tool can be developed to assist healthcare systems and physicians.

1 INTRODUCTION

The ongoing Coronavirus disease (COVID-19) pandemic has been in our lives for more than a year and all countries of the world have been trying to cope with this disease. Some countries have been successful in combating the epidemic and have almost managed to contain the epidemic. In some countries, the number of cases is increasing day by day and is still not controlled.

Information and data on coronavirus disease are increasing day by day with new patients and new findings. Due to the increasing volume of data generated by various sources, the healthcare industry has become highly data-driven. This industry is characterized by the complexity and variability of data. For the health sector to manage costs effectively and improve the quality of services, the right tools must be in place. Health analytics must be well applied to provide actionable insights and facilitate medical decision making.

The current pandemic presents us with an opportunity to improve our healthcare systems in the future. A major health event such as the COVID-19 pandemic can serve as an opportunity to improve our healthcare systems in the future. One of the most critical factors that we can improve upon during an outbreak is the distribution of medical supplies efficiently. Throughout the entire outbreak process, one of the main problems faced by healthcare providers is the lack of medical resources and an appropriate plan to distribute them efficiently.

The role of data and information has always been crucial to decision-making and healthcare delivery. In the event of an epidemic, even if the policies of countries to combat coronavirus disease are different, many common aspects need to be considered, researched and analyzed worldwide while combating this epidemic.

Prescriptive analytics is an approach that learns how to predict better outcomes through the use of machine learning. It works by asking: What changes can we make in response to our prediction of adverse events? The role of prescriptive analytics in medical decision making is emerging as an influential approach. Although Machine Learning models are widely used in epidemiological studies, their capabilities have not been adequately studied for COVID-19 (Chakraborti et al., 2021).

In these difficult times, being able to predict what kind of resource an individual will need, when tested positively, or before, will be of great help to the authorities as they can provide and adjust the necessary resources, and this prediction can save that patient's life.

In this study, the risk factors of coronavirus disease were examined and the findings in the literature were used. At this point, the goal of this study is to develop frameworks and algorithms that will enable physicians to make better predictions about patient by using prescriptive analytics and machine learning techniques. This study aimed to address the issue by adopting a machine learning model. Machine Learning models can help identify the most critical factors that contribute to the deaths and incidents caused by COVID-19. Also this study aims to highlight the effect of prescriptive analytics in meeting the needs of precision medicine.

2 DATA AND METHODOLOGY

First, all the factors that might have an effect on the COVID-19 are derived from literature. It was planned to benefit from the publications published in the literature and the open data published by the World Health Organization (WHO) on the basis of countries. In addition, many databases related to COVID-19 have been created and are being updated. The flowchart of this study can be seen in Figure 1.

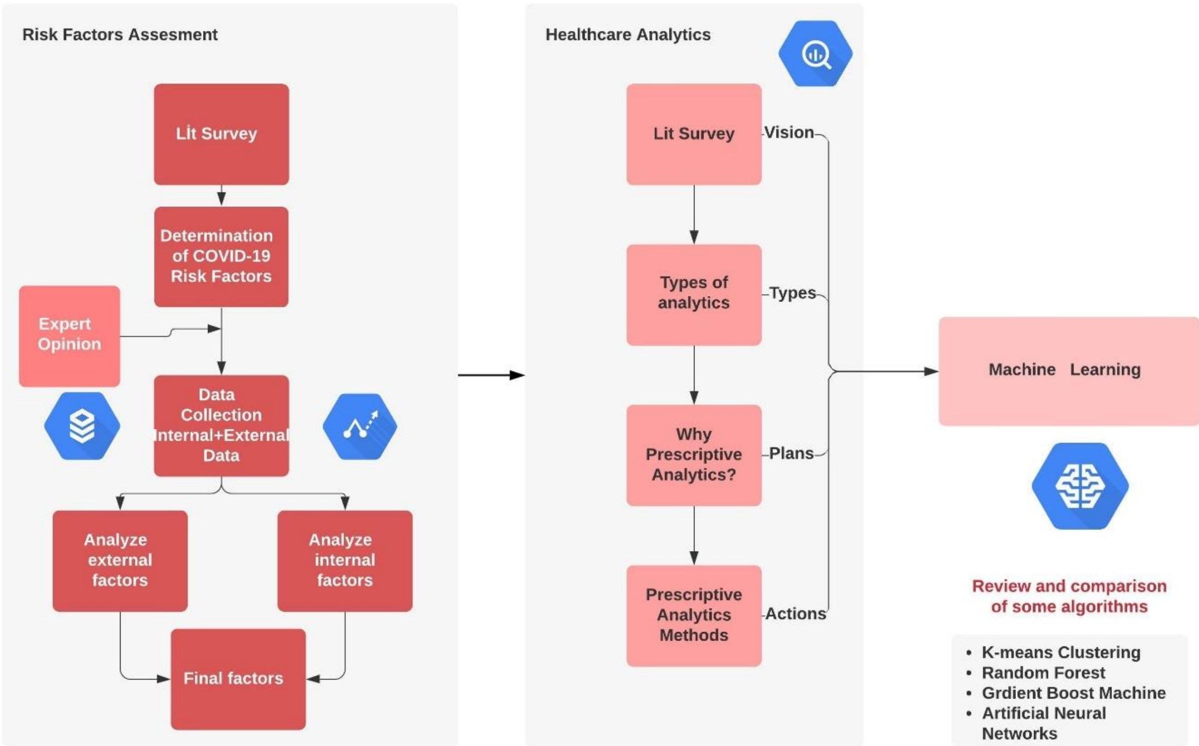

Figure 1: Flowchart of Methodology

In this thesis, the dataset contains one of COVID 19 Open-databases in Mexico information from the Epidemiological Surveillance System for Viral Respiratory Diseases. Included information corresponds only to data from epidemiological investigation of a suspected case of viral respiratory disease at diagnosis in the medical units of the Health Sector. According to the clinical diagnosis at the time of admission, the patient is considered as outpatient or inpatient. The database does not include developments during stay in medical units.

A dataset published by the Mexican government was obtained, containing a large amount of anonymized information on COVID -19 patients. The original data included 566 602 patient records and 23 characteristics for each patient. However, at the same time, there were many unavailable feature results and empty cells in the data, so 5 features were eliminated and not included in the model. In order for the model to provide more accurate results, 18 features from 220 402 patients were added to the model after the data cleaning phase.

Final Risk Factors

After eliminating these 5 features, the remaining 18 risk factors are listed below. These are the features given in the dataset that characterize the patient.

The aim of this thesis is to predict whether or not patients will need intensive care unit according to these risk factors.Inputs,

1. "Gender: Identifies the sex of the patient.
2. Age: Identifies the age of the patient.
3. Num_days_sympthom: Identifies the date on which the patient's symptoms began.
4. Intubated: Identifies if the patient required intubation.
5. Pneumonia: Identifies if the patient was diagnosed with pneumonia.
6. Pregnancy: Identifies if the patient is pregnant.
7. Diabetes: Identifies if the patient has a diagnosis of diabetes.
8. Copd: Identifies if the patient has a diagnosis of COPD.
9. Asthma: Identifies if the patient has a diagnosis of asthma.
10. Inmsupr: Identifies if the patient has immunosuppression.

11. Hypertansion: Identifies if the patient has a diagnosis of hypertension.
12. Other_disease: Identifies if the patient has a diagnosis of other diseases.
13. Cardiovascular: Identifies if the patient has a diagnosis of cardiovascular disease.
14. Obesity: Identifies if the patient is diagnosed with obesity.
15. Renal_chronic: Identifies if the patient has a diagnosis of chronic kidney failure.
16. Tobacco: Identify if the patient has a smoking habit.
17. Covid_negative: Identifies the result of the test is negative.
18. Covid positive: Identifies the result of the test is positive."

Output; ICU (intensive care unit): Identifies if the patient required to enter an Intensive Care Unit.

2.1 Step 1: COVID-19 Risk Factors Assessment

COVID-19 literature is reviewed and 40 factors that could affect illness were identified. And then some expert opinions will be taken for excluding some factors.

Some underlying diseases that trigger COVID-19 found in the literature review are in the form of substances. They represent the potential risk of contracting COVID-19.

Table1. Risk factors from literature

• "Chronic kidney disease -Having dialysis or has severe (stage 5) long-term kidney disease [3] • Cancer [4] • Chronic lung diseases, including COPD (chronic obstructive pulmonary disease), asthma (moderate-to-severe), interstitial lung disease, cystic fibrosis, and pulmonary hypertension [4] • Dementia or other neurological conditions [5] • Stroke or cerebrovascular disease, which affects blood flow to the brain [6] • Mental disorders like schizophrenia, ADHD, autism, and cerebral palsy [7] • Down syndrome [7] • Diabetes (type 1 or type 2) [3] • Heart conditions (such as heart failure, coronary artery disease, cardiomyopathies or hypertension) [8] • Immunocompromised state (weakened immune system) [9] • Have been treated in the past 5 years for a cancer of the blood or bone marrow (such as leukemia, lymphoma or myeloma) [6] • Have been treated in the past 1 year for a cancer that did not start in the blood or bone marrow[6] • Solid organ or blood stem cell transplant [6] • HIV/AIDS [10] • Long-term use of prednisone or similar drugs that weaken your immune system such as steroids [11] • Sickle cell disease or thalassemia [12] • Having hemoglobin blood disorders like sickle cell disease (SCD) or thalassemia [13] • Substance use disorders (such as alcohol, opioid, or cocaine use disorder) [7] • Liver disease [3]	• People with disability [12] • Overweight and obesity [14] • Pregnancy and breastfeeding [12] • Smoking, current or former [15] • Older Age [16] • Gender[3] • Race and Ethnicity [12] • Essential workers- Doctors, nurses, Grocery store employees, mail carriers, bus drivers, and others also have important jobs that can't be done at home. "Another population besides healthcare professionals at risk of contracting COVID-19 and spreading the virus is essential workers" [9]. • Poor ventilation[17] • Malnutrition (indirect in low-income nations) and living in poverty- such as homeless people [17] • Living area- metropolises [18] • people in aged care facilities [19] • latitude [18] • air pollution [18] • wind speed [18] • the total number of participants in major sports events [18] • GDP per capita [18] • Weather temperature [18] • population density[18] • industrial city[20] • Sea level[20]"

2.2 Step 2: Healthcare Analytics

Healthcare analytics literature is reviewed and presented here. Analytics types are examined and why prescriptive analytics were chosen explained with its advantages. In addition, prescriptive analytics methods are mentioned here.

The rapid emergence and evolution of the healthcare industry has created enormous opportunities for the healthcare professionals and institutions to improve their operations and enhance the patient's health outcome. The emergence and evolution of the healthcare analytics has influenced the way the healthcare industry is presently practiced [21].

Health analytics is defined as the collection, organization, and manipulation of health and other medical data. It is supported by five major stages. Five types of healthcare analytics are used to analyse the healthcare data. These include descriptive healthcare analytics, which are used for uncovering meaningful patterns, and health information modelling, which are used for developing and implementing evidence-based practices.

An example of such applications is when a healthcare professional uses a smartphone to detect a person's health condition in real-time. The outcome is not enough to inform the user about the most effective and actionable method. Due to the complexity of the data and its fragmentation, it becomes difficult for healthcare professionals to make informed decisions regarding the most appropriate treatment. This process is also referred to as medical decision making.

Due to the increasing popularity of predictive healthcare analytics, it has become a transforming tool for the daily healthcare industry. For example, by identifying individuals at risk for various diseases, it can predict the onset and severity of illness. Prescriptive analytics provide answers to commonly asked questions such as “what should we do” and “what should we avoid doing” according to the insights provided by the other three analytics.

3 PRESCRIPTIVE ANALYTICS IN HEALTHCARE

Prescriptive analytics are the most advanced type of analytics that evaluate the alternatives for balancing goal attainment. “They use various techniques such as optimization, simulation, heuristics, and multi-criteria decision making, and also enablers (e.g., deep learning, cognitive computing, and big data) to evaluate the results.” [22] The guiding references in the study are given in the Table 2.

Table 2: Literature Review on prescriptive analytics in healthcare

Author	Year	Title	Objective
Bohr, Adam Memarzadeh, Kaveh [25]	2020	“Current healthcare, big data, and machine learning”	To investigate the existing system
Mosavi, Nasim Sadat Santos, Manuel Filipe [22]	2020	“How prescriptive analytics influences decision making in precision medicine”	To highlight the efficient role of prescriptive analytics
Lepenioti, Katerina Bousdekis, Alexandros et al.[26]	2020	“International Journal of Information Management Prescriptive analytics : Literature review and research challenges”	To investigate the existing literature
Poornima, S. Pushpalatha, M. [23]	2020	“A survey on various applications of prescriptive analytics”	an updated survey on various applications of prescriptive analytics
Mehta, Nishita Pandit, Anil et al. [27]	2019	“Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study”	to study of big data analytics and artificial intelligence in healthcare
Schwartz, Ira M Nowakowski-sims, Eva et al. [28]	2017	“Predictive and prescriptive analytics, machine learning and child welfare risk assessment: The Broward County experience”	to develop a predictive model

3.1 Why Prescriptive Analytics?

Prescriptive analytics relies on the power of artificial intelligence techniques, which allow computers to process large amounts of data requiring no human input. Computer programs adjust automatically to take advantage of the new data that becomes available. This process is far more comprehensive and faster than the capabilities of humans.

Prescriptive analytics is another type of data analytics that uses statistical modelling and predictive analysis to evaluate future performance. It works by estimating what the future will look like based on current and historical data sets and what is likely to happen and then provide a recommendation on how to proceed. Using prescriptive analytics can help identify the most likely course of action to take in the event of a change in conditions.

3.2 Artificial Neural Network Methodology

ANN, which is an intelligent mathematical algorithm, consists of three main parts. These are the input layer, the middle or hidden layer(s), and the output layer. The first structure, the input layer, consists of the inputs to the system. The second structure, the hidden layer, represents the center of the artificial neural network and consists of many substructures called neurons. Within these neurons, the main mathematical calculations take place to process the inputs and provide the correct outputs accordingly. It functions just like a biological neuron in a real brain. The neurons in this layer are responsible for taking a set of values from the previous layer and sending them to the next layer. The values received and sent by the neuron may differ depending on the weight value of the wire leading to the neuron and carrying the value from the neuron.

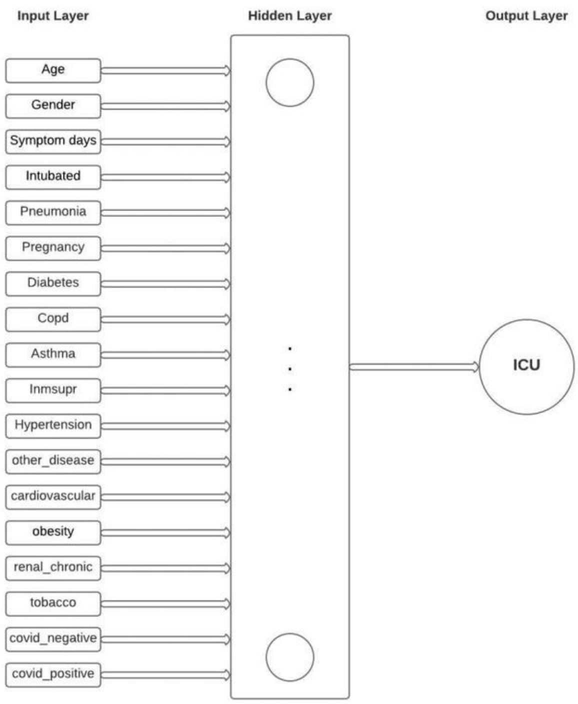

Figure 2. ANN Model representation

4 APPLICATION

The original data included 566,602 patient records and 23 characteristics for each patient. At the same time, however, there were many unavailable feature results and empty cells in the data, so 5 features were eliminated and not included in the model. In order for the model to provide more accurate results, 18 features from 220,402 patients were added to the model after the data cleaning phase. These characteristics are risk factors that determine the patient's need for an ICU.

The factors Id, entry_date, date_symptoms, date_died, covid_res were removed from the data. Instead of covid_res, two new factors were added cov_positive and cov_negative. Finally, 18 factors were added to the model. Columns = ["'sex', 'age', 'num_days_symptoms', 'intubed', 'pneumonia', 'pregnancy', 'diabetes', 'copd', 'asthma', 'inmsupr', 'hypertension', 'other_disease', 'cardiovascular', 'obesity', 'renal_chronic', 'tobacco', 'covid_negative', 'covid_positive', 'icu' "]

The goal of numerical application is to predict whether the patient needs an ICU or not by looking at the patient's characteristics using artificial neural networks and the dataset described in the previous sections. With this prediction, hospital resources, equipment and medical staff can be directed to more efficient places, and patients' lives can be saved by timely diagnosis and treatment.

The model was built using Python 3.9 software. Keras and Tensorflow were used as libraries. A total of 220,402 patient data were randomly assigned, 70% for training and 30% for testing. The data were divided as follows; Xtrain: 154281, Xtest: 66121. The model is sequential. There are 18 inputs and one output is taken. The number of hidden layers was increased by trial and error. There is no standard in this process to get the best results.

A neural network is given input values to be trained with weight values set in the hidden layers during training. It outputs an estimate of the new input value, which is given to the model after training is complete. The weights in the hidden layers are updated using the training backscatter method to make better estimates and improve the performance of the model. The Figure 3 is one of the performance graphs showing the success rate of the trained model during training. The graph of training and validation losses is shown below:

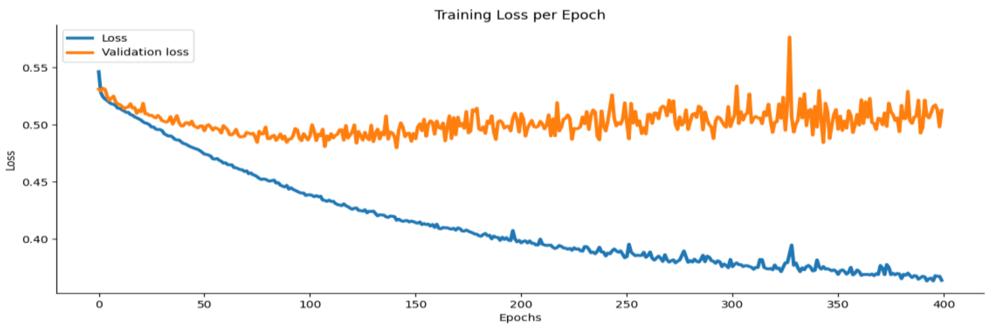

Figure 3: Schematic representation of training stages

In this diagram, there is clearly a healthy relationship between training loss and validation loss. Both seem to decrease up to a certain point and then remain at a constant value. This indicates that the model is well trained and means that it performs equally well for both training data and latent data. As the period increases, the loss value decreases. However, the difference between training loss and validation loss is striking. The training loss value was greater than the validation loss. As more period values increase, the gap in loss between training and validation increases.

The loss indicates how well the model understands the problem. In this graph, we can see that when the loss decreases, the training process is going well. As the model learns, the accuracy increases. To use this model to make predictions when given new data as input, the model.predict() function is used. Any test data can be selected and given as input. However, two sets of tests have been created for this model. These outputs are then shown graphically in the Figure 3.

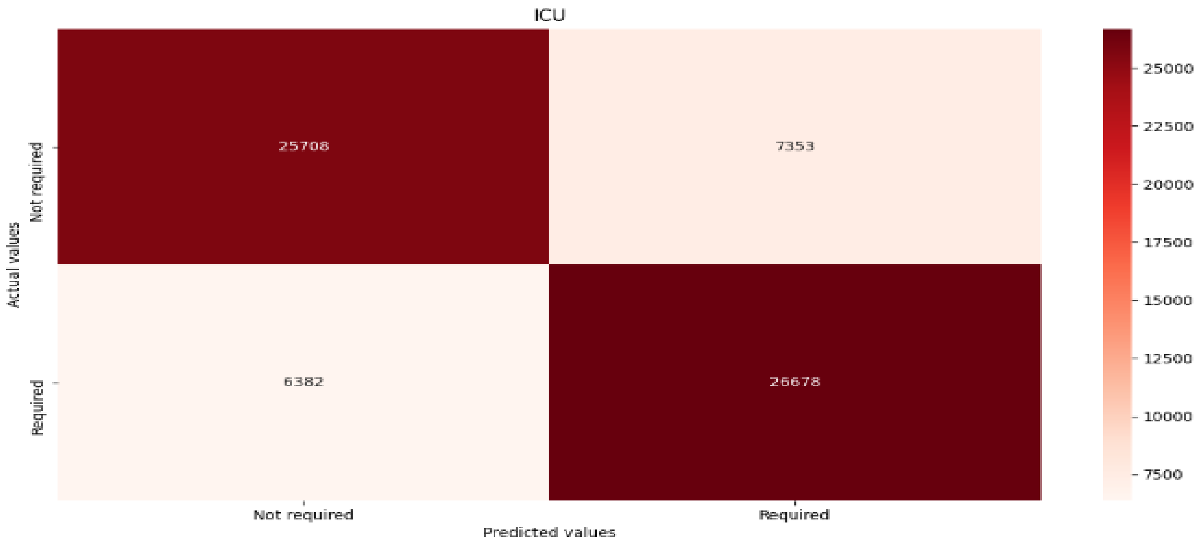

Figure 4: Graphical representation of the result

About this illustration: This model, created using ANN, predicts with high accuracy whether the patient will require intensive care. The model is more successful in predicting patients who need ICU at real values than patients who do not need ICU.

Recall: It measures the accuracy of the model in predicting all actual objects.

True Positive / (True Positive+ False Negative) = 78%

Precision: It indicates the percentage of true positives out of the total number of positive predictions.

True Positive / (True Positive+ False Positive) = 80%.

5 CONCLUSION

In this study, the usability of prescriptive analytics in epidemiological research was investigated using COVID -19 as an example. The main reason for using prescriptive analytics in this study is to analyse the data systematically as the analysis of increasing data becomes difficult as the epidemic progresses. COVID -19 risk factors have been studied in detail and the prediction has been performed using prescription analytics methods. For this purpose, artificial neural network algorithm is used.

With this study, it is possible to predict whether the patient needs intensive care depending on the characteristics of the patient. The goal is to predict whether the model, which learns from patient data in the dataset, will need an ICU when a new patient arrives. Thanks to this foresight, hospital resources, equipment and medical staff can be directed to more efficient places, and patients' lives can be saved through timely diagnosis and treatment. In this way, hospital managers and the government can see where the outbreak is going and then do capacity resource planning.

Artificial neural networks are mathematical models that can capture information and make determinations by mimicking human neurons. Traditional statistical methods cannot detect nonlinear relationships between different types of variables that involve complex relationships. The backpropagation method was used as a supervised learning algorithm. The predictive models were implemented using Python software.

For the model, the number of neural nodes in the hidden layer is decided experimentally and incrementally based on performance indicators. According to the applications, the number of neural nodes in the hidden layer in the model architecture was 17. The model was an 18x17x1 prediction model with 18 input layers, 17 hidden layers and 1 output layer. The original data of 220,402 patients are randomly divided into two parts of 70%, 30%. Training and testing data included patients with 154 281 and 66 121 respectively. After data cleaning and data processing in Python 3.9 software, these 18 features are available for 220 402 patients on patient basis. The prediction accuracy rate of the model is 79%.

REFERENCES

[1] S. Chakraborti *et al.*, "Evaluating the plausible application of advanced machine learnings in exploring determinant factors of present pandemic: A case for continent specific COVID-19 analysis," *Sci. Total Environ.*, vol. 765, p. 142723, 2021, doi: 10.1016/j.scitotenv.2020.142723.

[2] A. Trewartha *et al.*, "COVIDScholar: An automated COVID-19 research aggregation and analysis platform," *arXiv*, pp. 1–25, 2020.

[3] J. M. R. Wadhera, P. Wadhera, Gaba, Figueroa, Yeh, Shen, "Characteristics of Hospitalized Adults With COVID-19 in an Integrated Health Care System in California," pp. 2–5, 2020, doi: 10.1001/jama.2020.0757.

[4] H. M. Alger, J. H. Williams, J. G. Walchok, M. Bolles, G. C. Fonarow, and C. Rutan, "Role of Data Registries in the Time of COVID-19," *Circulation: Cardiovascular Quality and Outcomes*. Lippincott Williams and Wilkins, 2020, doi: 10.1161/CIRCOUTCOMES.120.006766.

[5] P. Medicine and W. Wars, "Personalized Medicine in Psychiatry impact of the pandemic on mental health," vol. 28, pp. 25–28, 2021, doi: 10.1016/j.pmip.2021.100077.

[6] E. Terpos *et al.*, "Hematological findings and complications of COVID-19," *American Journal of Hematology*, vol. 95, no. 7. Wiley-Liss Inc., pp. 834–847, Jul. 01, 2020, doi: 10.1002/ajh.25829.

[7] Q. Q. Wang, R. Xu, and N. D. Volkow, "Increased risk of COVID-19 infection and mortality in people with mental disorders: analysis from electronic health records in the United States," *World Psychiatry*, vol. 20, no. 1, pp. 124–130, 2021, doi: 10.1002/wps.20806.

[8] K. Roedl *et al.*, "Mechanical ventilation and mortality among 223 critically ill patients with coronavirus disease 2019: A multicentric study in Germany," *Aust. Crit. Care*, no. xxxx, 2020, doi: 10.1016/j.aucc.2020.10.009.

[9] M. Allam *et al.*, "COVID-19 diagnostics, tools, and prevention," *Diagnostics*, vol. 10, no. 6. MDPI AG, Jun. 01, 2020, doi: 10.3390/diagnostics10060409.

[10] Y. Hao, T. Xu, H. Hu, P. Wang, and Y. Bai, "Prediction and analysis of Corona virus disease 2019," *PLoS One*, vol. 15, no. 10 October, Oct. 2020, doi: 10.1371/journal.pone.0239960.

[11] D. J. Wooding and H. Bach, "Treatment of COVID-19 with convalescent plasma: lessons from past coronavirus outbreaks," *Clin. Microbiol. Infect.*, vol. 26, no. 10, pp. 1436–1446, 2020, doi: 10.1016/j.cmi.2020.08.005.

[12] M. C. OAKES *et al.*, "Pregnancy as a risk factor for severe coronavirus 2019 (COVID-19) disease using standardized clinical criteria," *Am. J. Obstet. Gynecol. MFM*, vol. 3, no. 3, p. 100319, 2021, doi: 10.1016/j.ajogmf.2021.100319.

[13] T. Levy *et al.*, "Development and Validation of a Survival Calculator for Hospitalized Patients with COVID-19," *medRxiv Prepr. Serv. Heal. Sci.*, 2020, doi: 10.1101/2020.04.22.20075416.

[14] A. S. Yadaw, Y.-C. Li, S. Bose, R. Iyengar, S. Bunyavanich, and G. Pandey, "Clinical predictors of COVID-19 mortality.," *medRxiv Prepr. Serv. Heal. Sci.*, May 2020, doi: 10.1101/2020.05.19.20103036.

[15] Z. Zheng, F. Peng, B. Xu, J. Zhao, H. Liu, and J. Peng, "Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the

novel coronavirus COVID- 19 . The COVID-19 resource centre is hosted on Elsevier Connect , the company ' s public news and information ," no. January, 2020.

[16] J. S. Brandt *et al.*, "Epidemiology of coronavirus disease 2019 in pregnancy: risk factors and associations with adverse maternal and neonatal outcomes," *Am. J. Obstet. Gynecol.*, pp. 1–9, 2020, doi: 10.1016/j.ajog.2020.09.043.

[17] N. Albayati, B. Waisi, M. Al-furaiji, M. Kadhom, and H. Alalwan, "Effect of COVID-19 on air quality and pollution in different countries," *J. Transp. Heal.*, vol. 21, no. March, p. 101061, 2021, doi: 10.1016/j.jth.2021.101061.

[18] W. Cao *et al.*, "Important factors affecting COVID-19 transmission and fatality in metropolises," *Public Health*, vol. 190, pp. e21–e23, 2021, doi: 10.1016/j.puhe.2020.11.008.

[19] J. Summers *et al.*, "The Lancet Regional Health - Western Pacific Potential lessons from the Taiwan and New Zealand health responses," vol. 4, no. August, 2020, doi: 10.1016/j.lanwpc.2020.100044.

[20] K. Aabed and M. M. A. Lashin, "Saudi Journal of Biological Sciences An analytical study of the factors that influence COVID-19 spread," *Saudi J. Biol. Sci.*, vol. 28, no. 2, pp. 1177–1195, 2021, doi: 10.1016/j.sjbs.2020.11.067.

[21] S. S. Blessy Trencia Lincy and N. Suresh Kum, *Transforming healthcare via big data analytics*. Elsevier Inc., 2018.

[22] N. S. Mosavi and M. F. Santos, "How prescriptive analytics influences decision making in precision medicine," *Procedia Comput. Sci.*, vol. 177, pp. 528–533, 2020, doi: 10.1016/j.procs.2020.10.073.

[23] S. Poornima and M. Pushpalatha, "A survey on various applications of prescriptive analytics," *Int. J. Intell. Networks*, vol. 1, no. August, pp. 76–84, 2020, doi: 10.1016/j.ijin.2020.07.001.

[24] J. Lopes, T. Guimarães, M. F. Santos, J. Lopes, T. Guimarães, and M. F. Santos, "ScienceDirect ScienceDirect Predictive and Prescriptive Analytics in Healthcare : A Survey Predictive and Prescriptive Analytics in Healthcare : A Survey," *Procedia Comput. Sci.*, vol. 170, pp. 1029–1034, 2020, doi: 10.1016/j.procs.2020.03.078.

[25] A. Bohr and K. Memarzadeh, *Current healthcare, big data, and machine learning*. INC, 2020.

[26] K. Lepenioti, A. Bousdekis, D. Apostolou, and G. Mentzas, "International Journal of Information Management Prescriptive analytics : Literature review and research challenges," *Int. J. Inf. Manage.*, vol. 50, no. April 2019, pp. 57–70, 2020, doi: 10.1016/j.ijinfomgt.2019.04.003.

[27] N. Mehta, A. Pandit, and S. Shukla, "Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study," *J. Biomed. Inform.*, vol. 100, no. October, p. 103311, 2019, doi: 10.1016/j.jbi.2019.103311.

[28] I. M. Schwartz, E. Nowakowski-sims, A. Ramos-hernandez, and P. York, "CE Do Not Cite or Quote Without Permission," *Child. Youth Serv. Rev.*, 2017, doi: 10.1016/j.childyouth.2017.08.020.

[29] S. Srinivas and A. R. Ravindran, "Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: A prescriptive analytics framework," *Expert Syst. Appl.*, vol. 102, pp. 245–261, 2018, doi: 10.1016/j.eswa.2018.02.022.