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A Bayesian belief network for risk assessment of Covid-19 in Nigeria, A case study of University of Abuja Teaching Hospital

Kalu Dike Uma, Oguntade, E.S, *Oladimeji D.M

Abstract

This study explored the risk assessment of a severe acute respiratory syndrome corona virus 2 (Sars-Cov2) disease in Nigeria using a Bayesian probability network approach. The data for this study were based on 617 Sars-Cov2 patients, taking into consideration symptoms displayed and other comorbidities. Using Dirichlet prior and multinomial distribution, the study assessed the risk of fever, cough, sore throat, shortness of breath, headache and anosmia; and other comorbidities such as hypertension, diabetes mellitus and asthma to the severity (asymptomatic, mild, moderate, severe) of coronavirus disease (covid-19) conditions. The study revealed that shortness of breath, cough and fever had the highest effect on the severity condition of covid-19. Also the study discovered that, headache, sore throat, vomiting and anosmia does not have direct correlation to severe covid-19 condition; thus where such occur, it may be due to chance. Furthermore, in the presence of comorbidities, shortness of breath, fever and cough highly increased the severity of covid-19 conditions of the patients studied. This study shows the risk posed by various covid-19 symptoms and comorbidity conditions to individuals in the study area. This in turn could be used as a safety measure for individuals and governments to formulate effective control and prevention strategies of covid-19.

Kalu Dike Uma, Oguntade, E.S, *Oladimeji D.M
Department of Statistics, University of Abuja, Nigeria,
**oladimejidamilare@yahoo.com *Phone number: +2347032325611*

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1. Introduction

In recent years, there have been diverse range of controversies and crises regarding health and health risks issues, as new sickness, diseases and health challenges emerge almost on daily basis carrying with them so many risk factors. For instance, there was the outbreak of Ebola in the Democratic Republic of Congo and other Central African Countries in 2014 that led to the death of thousands of persons in those countries and few persons in Nigeria (Althaus, Low, Musa, Shuaib, & Gsteiger, 2015). There was also the Middle East Respiratory Syndrome Coronavirus (MERS-COV) which was a regional epidemic in the Middle East(Killerby,et al 2020) and the most recent novel Coronavirus disease 2019 (Covid-19) which emanated from the city of Wuhan in China (Adeniran, Oguntade, Anjorin, & Ajagbonna, 2021). Every of these diseases came with their own risks, health challenges and dangers often leading to high mortality rates.

These health crises have led to increased recognition of the need for improvement in health risks assessment, health risk communication, health risk mitigation and health risk management(Boldog et al., 2020). Thus, with these, it had become imperative to improve on the methods of handling uncertainties in health risk assessment, to aid decision makers, public health professionals and the general public in making better informed decisions regarding health risks factors and issues.

In February 2020, the covid-19 disease found its way into Nigeria through an Italian traveler(Amzat et al., 2020). Since the introduction of the disease into Nigeria, the country has recorded over 200,000 cases; out of which over 180,000 have been successfully treated and 2067 recorded deaths according to Nigeria Centre for Disease Control (NCDC; Wednesday 26 May, 2021). Following the outbreak, there have been frantic efforts world over in assessing the risks associated with the disease.

Some researchers have used the conventional and frequentist methods in the analysis of risk, especially in the health sector. Such as the study of risk of ebola disease by Robert *et al.* (2019) where they applied regression in the study. Another of such was the study of Zika virus infection and risk of Guillain-Barré syndrome by Bautista (2019), where they applied time series in the risk study. But unfortunately, due to newness of coronavirus 2019 and the lack of data, application of these conventional and frequentist approaches may not necessarily yield the desired results, as they rely heavily on the availability of data. Hence, this study seeks to use a different approach to the risk of covid-19 in Nigeria. This approach was so chosen because it can be used when data is not readily available and the model can be updated as the new data and other relevant information become more available. Hence, this study adopted the Bayesian belief network to study the risk assessment of covid-19 in Nigeria.

2. Methods

2.1 Data Source

The data used for the study was secondary data gotten from the University of Abuja Teaching Hospital, Abuja. The data contained daily testing, confirmed, treated and death cases of Covid-19 patients. The data span the period of February 2020 to August 2021. The data obtained contain information on patients' symptoms at presentation alongside with sex, age and other underlying sicknesses.

2.2 A Bayesian Method and formulation of a Belief Network Influence diagram

A Bayesian probability shows how a degree of belief can be expressed in-terms of probability. The Bayes method relies on available information about the parameter "x" of interest. Based on this available information (prior), a future (posterior) probability/prediction is made.

Bayes' theorem is defined in 1.

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$$P(x \mid y) = \frac{P(y \mid x)P(x)}{P(y)} \tag{1}$$

where,

P(x) is the probability of event "x", called prior. That is probability of "x" happening without any information about event "y".

P($x|y$) is the conditional probability of event "x" happening given that event "y" has already occurred. This is called the "Posterior".

P($y|x$) is the conditional probability of event "y" happening given that event "x" has already occurred. It is called "Likelihood". And

P(y) is the probability of event "y" happening without any information about event "x". It is called "Marginal Likelihood".

One of the most used prior distribution is the conjugate prior. The conjugate prior have an advantage over other priors because they lead to posterior distribution in the same family of distribution as the prior.

A Dirichlet distribution with $\alpha = (\alpha_i, \ldots, \alpha_k)$ were selected as prior. The prior probability function is presented in 2.

$$p(\theta) = p(\theta \mid \alpha) = \frac{\Gamma(A)}{\prod_i \Gamma(\alpha_i)} \prod_i \theta_i^{\alpha_i - 1} \tag{2}$$

The conjugate Dirichlet prior has probability density function (pdf) proportional to

$$\prod_{i=1}^{k} \theta_i^{\alpha_i - 1}$$

where:

A $= \Sigma_{i=1}^{k} \alpha_i$ and $\alpha_i, \ldots\ldots, \alpha_k$ are parameters with $\alpha_i > 0$ for $i = 1, \ldots, k$

It can be written thus,

$$\frac{\Gamma(A)}{\Gamma(\alpha_1)\Gamma(A-\alpha_1)} \theta_1^{\alpha_1 - 1}(1-\theta_1)^{A-\alpha_1-1} \text{ x } \frac{\Gamma(A-\alpha_1)}{\Gamma(\alpha_2)\Gamma(A-\alpha_1-\alpha_2)} \frac{\theta_2^{\alpha_2-1}(1-\theta_1-\theta_2)^{A-\alpha_1-\alpha_2-1}}{(1-\theta_1)^{A-\alpha_1-1}}$$

$$\text{x.....x} \; \frac{\Gamma(A-\alpha_1-....-\alpha_{k-2})}{\Gamma(\alpha_{k-1})\Gamma(A-\alpha_1-....-\alpha_{k-1})} \frac{\theta_{k-1}^{\alpha_{k-1}-1}\theta_k^{\alpha_k-1}}{(1-\theta_1-....\theta_{k-2})^{\alpha_{k-1}+\alpha_k-1}} \tag{3}$$

Hence, our prior

$$p(\theta) = Dir(\theta \mid \alpha) = \frac{1}{B(\alpha)} \prod_i^k \theta_i^{\alpha_i-1} \tag{4}$$

Assume that $X_1,......,X_k$ with frequencies for categories 1, . . . , k,

N = $\sum_{i=1}^k X_i$ fixed with probabilities $\theta_1......\theta_k$; where $\sum_{i=1}^k \theta_i = 1$. Then X_1………X_k is multinomial with pdf

$$p(X_1 = x_1,........,X_k = x_k) = \frac{N!}{\Pi_{i=1}^m x_i!} \prod_{i=1}^k \theta_i^{x_i} \tag{5}$$

When k=2, the multinomial becomes Binomial (N,θ_1) with likelihood

$$L(\theta;x) = \frac{N!}{\Pi_{i=1}^k x_i!} \prod_{i=1}^k \theta_i^{x_i}$$

$$\propto \prod_{i=1}^k \theta_i^{x_i} \tag{6}$$

The conjugate Dirichlet prior has probability density function (pdf) proportional to

$$\prod_{i=1}^k \theta_i^{\alpha_i-1} \tag{7}$$

With posterior pdf

$$\prod_{i=1}^k \theta_i^{\alpha_i-1} \text{ x } \prod_{i=1}^k \theta_i^{x_i} \cong \prod_{i-1}^k \theta_i^{\alpha_i+x_i-1} \tag{8}$$

Similarly, let $X = (x_1,........,x_k)$, then the posterior distribution of θ given X= x

$$p(\theta \mid x) = \prod_{i=1}^k \theta_i^{\alpha_i+x_i-1} \tag{10}$$

Simplifying equation, the joint density function is thus,

$$f_1(\theta_1)f_2(\theta_2 \mid \theta_1)f_3(\theta_3 \mid \theta_1,\theta_2)......f_{m-1}(\theta_{m-1} \mid \theta_1,.....,\theta_{m-2}),$$

$$P(y \mid symptoms) = \int_x p(y \mid x, symptoms)p(x \mid symptoms)dx \tag{11}$$

where x represents data of the distribution and the symptoms (data) are assumed to be independent and identically distributed (iid).

Applying equation (1).

$$P(Covid-19 \mid fever) = \frac{p(fever \mid Covid-19)p(Covid-19)}{p(fever)} \tag{12}$$

Simplifying equation, the joint density function is thus,

$$f_1(\theta_1) f_2(\theta_2 \mid \theta_1) f_3(\theta_3 \mid \theta_1, \theta_2) \ldots\ldots f_{m-1}(\theta_{m-1} \mid \theta_1, \ldots\ldots, \theta_{m-2}),$$

$$P(y \mid symptoms) = \int_x p(y \mid x, symptoms)\, p(x \mid symptoms)\, dx \qquad (11)$$

where x represents data of the distribution and the symptoms (data) are assumed to be independent and identically distributed (iid).

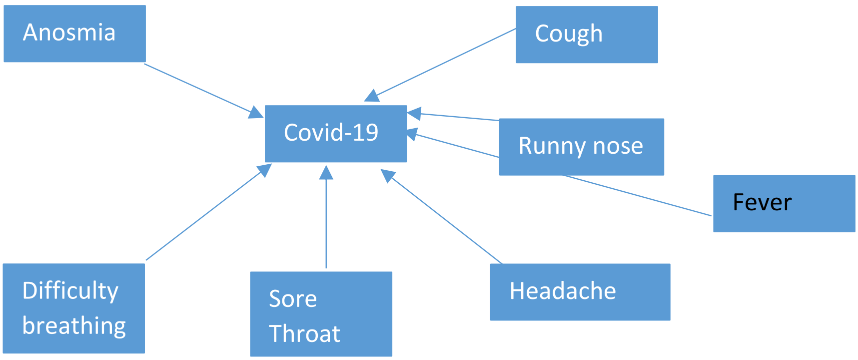
Applying equation (1).

$$P(Covid-19 \mid fever) = \frac{p(fever \mid Covid-19)\, p(Covid-19)}{p(fever)} \qquad (12)$$

Hence, the probability of risk of covid-19 detection is thus,

$$P(Covid-19\, detection) = p(Covid-19 \mid fever) + (1 - p(Covid-19 \mid fever)) + p(Covid-19 \mid cough) + \ldots.. + p(Covid-19 \mid Sorethroat)$$

Based on the available information, the influence diagram for this study is thus formulated in figure 1.



2.3 Ethical consideration

The data used for this present study were exclusively information on anonymous subjects from UATH. Nonetheless, approval was sought via writing and other ethical procedures followed to obtain the require data.

3 Results and Discussion

3.1 Demographic Characteristics of Covid-19 Patients

Table 1 displays the summary statistics (demographic distribution) of patients by age, sex, and comorbidities such as Hypertension (HTN), Diabetes mellitus (DM), cardiovascular disease, Asthma and Chronic kidney disease. The results indicated that 239 (38.6%) of the covid-19 patients received and treated at the facility were females while 350 (61.4%) were males. Also, 105(17%) of the studied patients were less than 35 years old, while 514 (83%) of the studied patients were 35 years and above. The table further revealed that 303 (49.9%) were Hypertensive, 17(2.8%) had some form of cardiovascular diseases, 180(29.1%) were diabetic patients, 20 (3.2%) were asthmatic and 30(4.9%) of the studied patients had chronic kidney disease (CKD).

	Frequency	Percent
AGE RANGE		
<35	105	17
>=35	514	83
SEX		
Male	350	61.4
Female	239	38.6
HTN		
Yes	303	49.9
No	316	51.1
CARDIOVASCULAR		
Yes	17	2.8
No	602	97.2
DIABETES		
MELLITUS		
Yes	180	29.1
No	439	70.9
ASTHMA		
Yes	20	3.2
No	439	70.9

The average age of the studied patients is 51 years old with range of 20 to 103 years old. Patients' average recorded temperature was 36.6°C while the minimum and maximum is 32 and 38 respectively. Average pulse rate was 93.8 and systolic BP and Diastolic BP were 133 and 84 respectively. The average oxygen saturation was 94% (Table 2).

Table 2: Summary of Patients' Clinical Quantitative Variables

	Temp (oC)	*HR*	*Systolic BP*	*Diastolic BP*	*SPo2%*	*Age*
Mean	36.588	93.879	133.197	84.274	93.512	50.953
Standard Error	0.0876	0.696562	0.869	0.572	0.393	0.667
Median	36.4	93	132	84	97	53
Mode	36.4	96	130	80	99	55
Standard Deviation	2.166	17.246	21.335	14.035	9.751	16.623
Kurtosis	522.690	0.906	0.206	1.285	10.412	-0.0429
Skewness	22.007	0.376	0.326	0.447	-2.999	-0.326
Minimum	32	26	74	43	32	20
Maximum	38	160	207	154	100	103

The Prior Probability of covid 19 Severity

Since Covid 19 is new disease and severity status is clinically determined this study make use of discrete uniform distribution as a prior distribution. Therefore, the prior probability of Covid 19 Severity is given in table 3.

Table 3: Prior probability of Covid 19 severity

	ASYMPTOMATIC	MILD	MODERATE	SEVERE
p(x)	0.25	0.25	0.25	0.25

3.2 A Joint Probability of Covid-19 Condition

The table 4 reveals joint probabilities between covid-19 clinical assessment and various symptoms. The joint probability of fever and asymptomatic patient was 0.065, 0.526f or mild, 0.647 for moderate and 0.719 for severe covid-19. Also, the table contains the joint probability of cough and covid-19; 0.487 who had cough also had mild covid-19, 0.487 were moderate, while 0.681 had cough and severe covid-19. 0.136 had sore throat and mild covid-19, 0.08 had moderate covid-19 with sore throat, and 0.088 had severe covid-19 with sore throat. 0.11 had mild covid-19 with runny nose, 0.033 had moderate covid-19 and runny nose, 0.038 had severe covid-19 with runny nose. In addition, 0.175 had mild covid-19 with shortness of breath, 0.493 had moderate covid-19 and shortness of breath, 0.563 had severe covid-19 with shortness of breath. 0.234 patients had mild covid-19 with headache, 0.093 had moderate covid-19 with headache, while 0.147 had severe covid-19 with headache (Table 3).

Table 4 : Joint Probability of Covid-19 Condition given the Various Symptoms

SYMPTOMS	ASSESSMENT%			
FEVER	Asymptomatic	Mild	Moderate	Severe
YES	6.5	52.6	64.7	71.9
NO	93.5	47.4	35.3	28.1
COUGH				
YES	3.9	48.7	64.7	68.1
NO	96.1	51.3	35.3	31.9
SORE THROAT				
YES	2.6	13.6	8	8.8
NO	97.4	86.4	92	91.2
RUNNY NOSE				
YES	2.6	11	3.3	3.8
NO	97.4	89	96.7	96.2
SHORTNESS OF BREATH				
YES	0	17.5	49.3	56.3
NO	100	82.5	50.7	43.7
HEADACHE				
YES	5.2	23.4	9.3	14.7
NO	94.8	76.6	90.7	85.3
ANOSMA				
YES	1.3	9.7	6	5.5
NO	98.7	90.3	94	94.5

3.3 A belief Network of Covid-19 risk Assessment

Table 5 shows the updated probabilities when a male patient that is above 35 years old and has any symptoms such as fever; cough with prior probability for Covid-19 status being (Asymptomatic, mild, moderate or severe) which is the posterior probability. The likelihood of patient clinical assessment of covid-19 given fever, for mild the likelihood increase from 25% to 37%, moderate decrease from prior of 24% to 18% and severe increased from 24% to 36%. Given cough, the likelihood of mild increased to 37%, moderate decreased to 19% and severe increased to 37%. For given that the patient has sore throat risk of mild decreased to 24%, risk of moderate increased to 29% while severe risk remains unchanged. For given Runny nose, the risk of mild increased to 31%, risk of moderate increased to 26%, risk of severe covid-19 decreased to 37%. For shortness of breath, the risk of mild reduced to 22.9%, moderate increased to 36%, while the risk of severe increased to 41%. Also, for Anosmia, the risk of mild increased to 29%, moderate increased to 36%, while the risk of severe increased to 34%.

Table 5: Risk assessment of covid-19 symptoms without comorbidities

ASSESMENT	FEVER	COUGH	SORE THROAT	RUNNY NOSE	HEAD ACHE	SHORTNESS OF BREATH	ANOSMIA
ASYMPTOMATIC	0.09	0.071	0.09	0.06	0.03	0.01	0.01
MILD	0.37	0.37	0.24	0.31	0.31	0.229	0.29
MODERATE	0.18	0.19	0.29	0.26	0.29	0.23	0.36
SEVERE	0.36	0.37	0.38	0.37	0.35	0.41	0.34

3.4 A Comorbidity and Clinical Assessment

Table 6 displays the updated probabilities when a male patient that is above 35 years old, who has at least one comorbidities and has any symptoms such as fever; cough, sore-throat with 'prior' probability for COVID19 status being (Asymptomatic, mild, moderate or severe) which is the posterior probability. The likelihood of patient clinical assessment of covid-19 given comorbidity and fever, for mild the likelihood increased to 27%, moderate decreased from prior of 24% to 23% and severe increased from 24% to 40%. Given comorbidity and cough the likelihood of mild decreased to 20%, moderate increased to 35% and severe increased 41%. For given comorbidity and sore throat the risk of mild decreased to 21%, risk of moderate increased to 35% while risk of severe risk increased to 41%. For given comorbidity and Runny nose, the risk of mild increased to 27%, risk of moderate increased to 28%, risk of severe covid-19 increased to 42%. For comorbidity and shortness of breath, the risk of mild reduced to 18%, moderate increased to 27%, while the risk of severe increased to 55%. Given comorbidity and Anosmia, the risk of mild reduced to 27%, risk of moderate reduced to 33% while the risk of severe covid-19 increased to 39%. Generally speaking, the presence of any comorbidity in a patient increased the severity of the covid-19 status e.g comorbidities risk increased severity of patient presented with fever from 36% to 41% also increased the risk of severity of patient presented with shortness of breath from 41% to 55%. Therefore, presence of comorbidities in covid-19 patients increase the risk of severity.

Table 6: Risk Assessment Probabilities with Comorbidities

ASSESMENT	Fever	Cough	Sore throat	Runny nose	Head Ache	Shortness of breath	Anosmia
ASYMPTOMATIC	0.1	0.04	0.03	0.03	0.05	0	0.01
MILD	0.27	0.20	0.21	0.27	0.28	0.18	0.27
MODERATE	0.23	0.35	0.35	0.28	0.28	0.27	0.33
SEVERE	0.41	0.41	0.41	0.42	0.39	0.55	0.39

3.5 Discussions

The study showed that the average age of the studied patients was 51 years old. Patients' average temperature was 36.6°C. Average pulse (heart beat) rate was 93.8 and systolic BP and Diastolic BP were 133 and 84 respectively (Table 2). The average oxygen saturation (amount of oxygen traveling through the body with red blood cells) was 94%. The studied patients' characteristics further showed that 239 (38.6%) were females while 350 (61.4%) were males (Table 1). Also it further revealed the presence of comorbidities as 303 (49.9%) were Hypertensive, 17(2.8%) had cardiovascular disease, 180(29.1%) were diabetic, 20 (3.2%) were asthmatic and 30(4.9%) of the studied patients had some form of CKD. This result of this study agrees with (Adeniran et al., 2021). The study revealed more covid-19 cases in male than female. Also, presence of comorbidity conditions has been identified as one of the factors causing complications in covid-19 patients (see table 6). This is in line with a related study on second cancer occurrence in Nigeria(Oguntade & Oladimeji, 2020).

The result indicated that presence of cough in a patient increased risk of moderate to severe covid 19. The result is consistent with Soares, Mattos, and Raposo (2020) and Imran *et al*. (2020) who asserted that cough increases the risk of covid-19 in Brazil. The study further revealed that fever increased the risk of covid-19 also. This also is in tandem with Leung (2020) and Soares *et al*. (2020) who opined that fever increased the risk of covid-19 in Europe.

Furthermore, the outcome of the study revealed that shortness of breath was associated with moderate to severe cases of covid 19 (Table 7). This result agrees with Zheng *et al.* (2020) who studied the risk of covid in China and discovered shortness of breath was high risk factor of covid.

But contrary to popular belief and in contrast with Soares *et al*. (2020) that suggested headache, runny nose and vomiting were symptoms of covid. These sicknesses do not necessarily correlate with the risk of covid-19 compare to cough, sore throat and shortness of breath (Table 3), as their conditional probabilities were seen to be inconsistently changing with covid-19 severity.

In addition, patients with comorbidities such as hypertension, asthma and diabetes mellitus tend to be down with more severe covid-19 than the patient who has no comorbidities (Table 5). The finding of this present study is consistent with other related study in Nigeria(Adeniran *et al.,* 2021). The authors submitted that patient with comorbidity conditions are more likely to experience the disease.

4. Conclusion

A risk assessment system of novel coronavirus is presented based on Bayesian Belief network. The study concludes that cough, fever and shortness of breath increased the risk of moderate to severe covid 19. Patients with comorbidities such as hypertension, asthma and diabetes mellitus in the presence of these symptoms (fever, cough and shortness of breath) tend to be down with more severe covid-19 than the patient who has no comorbidities. Therefore, government efforts should be geared towards prevention rather than treatment of the disease. Hence, public awareness is needed for the populace especially those with other comorbidity conditions.

Conflicts of interest
None declared

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