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Development of a Bayesian Subjective Model for Predicting the Clinical Diagnosis of Ebola in the Democratic Republic of the Congo

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Abstract

The symptoms and clinical signs of Ebola virus disease are similar to those of malaria, thus leading to difficulties in terms of making differential diagnoses. Therefore, we developed a subjective model for the clinical diagnosis of Ebola. Excel and SPSS software were used to an-alyse data. The likelihood ratio, the kappa statistic and various internal evaluation parameters of the model were calculated. These analyses revealed that 4 factors strongly influence the clinical diagnosis of Ebola: haemorrhagic signs, neurological signs, digestive signs and epidemiological links. Among these 4 factors, the combination of haemorrhagic signs and epidemiological links in a patient yields a 60.5% chance of the case being confirmed as Ebola. Therefore, all health care providers in areas with the potential for Ebola must prioritise classifying any patient with these 2 factors as a genuine case of Ebola

Keywords: Internal Validation; Subjective Bayes Model; Clinical Diagnosis; Ebola

Introduction

Ebola virus (EBOV) causes acute and severe illness. This virus was first identified in 1976 during 2 simultaneous outbreaks in South Sudan and the Democratic Republic of Congo (D.R.C.)1. Subsequently, there have been more than 25 outbreaks of Ebola virus disease (E.V.D.), mainly in Central and West Africa. West Africa accounts for the greatest number of E.V.D. pa-tients. Between 1976 and 2022, the DRC reported 15 epidemics of EVD. Of these, the tenth epidemic, which affected the provinces of North Kivu and Ituri, remains the longest-running in the DRC. Globally, it is the second longest and deadliest epidemic after the one in West Africa in 20142,3.

This 10th epidemic in the D.R.C. lasted 695 days (23 months) and resulted in 3,470 cases and 2,280 deaths, with a case fatality rate of 66%.

During all of these Ebola epidemics, healthcare providers thought that the patients were suffering from malaria. The correct diagnosis was only made after EVD began to lead to deaths.

The literature on previous epidemics shows that healthcare workers are more exposed to E.V.D. than the general population. During the 1995 Ebola epidemic in the D.R.C., 80 out of 315 health workers involved in the response (25%) contracted the disease4.

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The cumulative incidence of Ebola virus infection in this population was 42.2 times higher than that in non-health workers5.

For example, some experts have reported that the large-scale threat of E.V.D. is limited to countries with weak public health systems6.

Ebola virus infection among humans initially manifests as nonspecific symptoms such as fever, vomiting, and severe diarrhoea. These symptoms do not necessarily suggest E.V.D. infec-tion. Doctors working in malaria-endemic regions such as the D.R.C. believe that malaria can promote the spread of E.V.D., thus highlighting the importance of careful differential diagnosis and laboratory confirmation for patients presenting with such symptoms.

Ebola virus disease and malaria share a common and significant sign: fever. However, malaria is the leading cause of healthcare visits in our communities in general and in the Beni health zone in particular. During E.V.D. epidemics, malaria diagnoses became syndromic to minimise the risk of E.V.D. contamination. Syndromic diagnosis of malaria can result, among other things, in the overreporting of cases. This overreporting of cases may lead to nosocomial infections due to contact between people who have come for treatment, those accompanying them, and even healthcare staff.

Given the rapid spread of E.V.D. and its symptoms, which are similar to those of malaria, it is essential to establish a diagnostic model for the clinical diagnosis of E.V.D.

The results of this study will help field epidemiologists and service providers properly triage cases, especially in areas at risk of an Ebola epidemic.

The D.R.C. has continental dimensions, and the similarity between the signs/symptoms of E.V.D. and those of malaria means that an early warning system for E.V.D. is essential. This system will help healthcare providers take precautions and predict the likelihood of the presence of the Ebola virus based on patients' symptoms.

Moreover, our health facilities are in an advanced state of disrepair, characterised by a lack of adequate equipment and specialised laboratories to ensure reliable results in the context of E.V.D.

To confirm a case of E.V.D., the sample taken should be sent to the laboratory of the Na-tional Institute for Biomedical Research (I.N.R.B.) in Kinshasa, the country's capital, for con-firmation. Given the distance between North Kivu and Kinshasa, the time it takes to conduct the tests is long, thus making contact tracing complex in the context of limited resources.

Therefore, a prediction model is essential as an early warning tool. Healthcare providers must use prediction models to enable the rapid isolation of cases and to manage all suspected cases of Ebola virus disease.

Numerous studies have been carried out to predict detection. However, these methods have been carried out on fragmented datasets with limited generalizability. The aim of this study is to create a more generalizable model using a Bayesian approach.

In short, the results of this study will help to efficiently triage of patients with E.V.D. based on clinical characteristics. They will also make it possible to improve the triage algorithm to avoid nosocomial infections caused by E.V.D.

Methods

Study design

This retrospective study used expert opinions in the epidemiological surveillance of Ebola virus disease in the Democratic Republic of the Congo. These experts participated in the E.V.D. response from West Africa in 2015 and Eastern D.R.C. (North Kivu, South Kivu and Ituri) in 2018. The opinions revolved around the clinical signs and symptoms of E.V.D. in suspected cases. Each expert listed the clinical signs and symptoms. The experts reached a consensus on the clinical signs and symptoms. The clinical signs and symptoms were grouped into independent and mutually exclusive factors. Once the clinical signs and symptoms had been grouped into independent factors, each expert was asked to predict the clinical diagnosis based on the signs and symptoms and using the principles of probability. All these probabilities were used to cal-culate the a priori probability quotient (Q.A.P.R.I.) of the confirmed clinical diagnosis of E.V.D. An abacus was used for a numerical representation to simplify the prediction of the diagnosis as a function of factors/symptoms or clinical signs. This chart provides the different likelihood ratios for each factor in relation to the confirmation of the diagnosis of E.V.D. The likelihood ratio and the Q.A.P.R.I. that were used to calculate the post hoc probability quotient (Q.A.P.O.) to deter-mine the probability of having E.V.D. confirmed in a patient with a certain combination of dif-ferent factors (clinical signs and symptoms). The results of these different probabilities were validated internally.

For internal validation, we calculated the degree of agreement within and between the experts. The discrimination criterion (cut-off point), sensitivity (Se), specificity (Sp), positive predictive value (PPV), and negative predictive value (N.P.V.) were calculated by comparison with the subjective Bayes model. Finally, the experts reached a consensus based on the 42 hy-pothetical cases that were generated.

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Data collection

A paper questionnaire was used to collect the opinions of the various experts who took part in the study. The experts were recruited from epidemiological surveillance teams.

Signs and symptoms

The active and passive search for suspected or alert cases of E.V.D. was based on specific clinical signs and symptoms that the Ministry of Public Health, Hygiene and Social Welfare had listed in its strategic plan for the response to EVM in 2019 in Eastern D.R.C.2. Several studies have highlighted some of the clinical signs and symptoms of E.V.D. in the D.R.C. and West Af-rica using other approaches for analysis11-15. The most consistent criteria for a suspected case of Ebola in all countries affected by the disease were fever, unexplained bleeding, sudden death, and previous contact with a person suspected, probable, or confirmed of having E.V.D.16. However, Desclaux et al.17 reported that symptoms of M.V.E. are not permanently present and that 10% of E.V.D. cases do not present with fever18.

The team of epidemiologists in Equateur Province in April–May 2018 (D.R.C.) investi-gated all cases of E.V.D., and the most frequently reported signs/symptoms in people with con-firmed or probable E.V.D. were fever (40 [95%] out of 42 cases), general and intense fatigue (37 [90%] out of 41 cases), and loss of appetite (37 [90%] out of 41 cases). Gastrointestinal symptoms were also frequently reported, and 14 (33%) out of 43 people reported the following signs of haemorrhage19.

In another prospective quantitative observational study of E.V.D. in 2012 in the popula-tion of the town of Isiro in Haut-Uélé Province, out of 52 patients, the majority of those treated at the Ebola treatment centre (E.T.C.) experienced fever (55.6%) during their stay in the hospital20. The main symptoms experienced by E.T.C. patients during their hospital stay included asthenia (82.4%), anorexia (82.4%), myalgia (70.6%), sore throat/difficulty swallowing (70.6%), arthral-gia (76.5%) and nausea (70.6%). Gastrointestinal signs and symptoms (nausea, diarrhoea, vom-iting) (76.4%) and general aches and pains (94.1%) were common in patients admitted to the E.T.C.20.

In her paper on predicting Ebola virus infection, Mary-Anne Hartley stated that nonspe-cific symptoms of E.V.D. pose a major problem for triage and isolation efforts in Ebola treatment centres. A better understanding of the statistical relevance of individual triage symptoms is es-sential in low-resource settings where rapid, laboratory-confirmed diagnoses are often unavail-able21.

Inclusion criteria

The criteria for inclusion in the study were to be an expert in the epidemiological sur-veillance of E.V.D., to have accepted the invitation, and to be available during the study period. Emphasis was placed on participating in the E.V.D. response in West Africa (in 2014) and in the eastern part of the D.R.C. (in August 2018).

Data entry

Expert opinions were entered into Microsoft Excel for all 42 hypothetical cases, with the probability of developing the disease based on clinical signs and symptoms. Consensus data were also entered using the same software.

Primary data

The primary data in this study consisted of the opinions of Ebola experts from epidemi-ological surveillance of confirmed cases of E.V.D. based on clinical signs and symptoms.

Data analysis

Microsoft Excel was used to program all the Bayes mathematical modelling formulae and to perform certain statistical calculations, such as determining the kappa value to measure the agreement between experts. Bayesian model for Ebola diagnosis and model validation

The Bayesian mathematical model for predicting the diagnosis of Ebola began by draw-ing up a list of factors thought to underlie the phenomenon to be studied. Based on these factors, the Q.A.P.R.I. was calculated.

Results

The E.V.D. diagnostic model

According to experts in epidemiological surveillance in the D.R.C., the factors or symptoms/clinical signs of E.V.D. are grouped into seven factors according to the independent and mutually exclusive elements in Table 1 in the annex. The a priori probability quotient was calculated on the basis of the probabilities of a clinical diagnosis based on the clinical signs/symptoms expressed by the experts in the following Table 2 in the annex.

$$QAPRI = \frac{P(MVE+)}{P(MVE-)} = \frac{0{,}69}{0{,}31} = 2{,}18$$

The expert prediction indicates that each patients with one of the abovementioned factors has a greater chance of being E.V.D. positive.

The likelihood ratios shown in Table 3 measure the impact of each factor on the occurrence of EVD in a patient.

The further the R.V. value is from 1, the greater the likelihood that the patient has E.V.D., according to the results of the chart.

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Given that we have calculated the a priori probability of a patient having EVM with some or all of the factors present (Q.A.P.R.I.) and the likelihood ratio (L.R.), the a posteriori probability (Q.A.P.O.) that the patient is actually positive for EVM gives the following results when all 7 factors are present in the Ebola patient and when all 7 factors are absent in the Ebola patient.

Table 1: Predictive factors of E.V.D. according to the opinions of epidemiological surveillance experts.

N°	Factors (signs/symptoms) of a patient suffering from E.V.D.	Grouping of factors (into independent and mutually exclusive elements)	Operational definition
1	Signs of bleeding	Haemathemese	Any patient presenting with at least 1 instance of bleeding involving at least 1 organ (skin, lungs, urine, nose, etc.)
		Red eyes	
		Icterus	
		Bleeding gums	
		Hepatitis	
		Genital haemorrhage	
		Abortions	
		Bleeding from injection sites	
		Melena	
		Haemoptysis	
2	Neurological signs	Coma	All the signs and symptoms indicate damage to the nervous system
		Convulsion	
		Cephalus	
3	Digestive signs	Diarrhoea	Any patient with at least 1 sign of digestive system damage
		Vomiting	
		Anorexia	
		Abdominal pain	
		Epigastralgia	
4	Pain syndromes	Myalgia	Any patient reporting localised or generalised pain
		Arthralgia	
		Chest pain	
5	General signs	Asthenia	Any patient with a deterioration in general condition
		Fever	
		Dehydration	
6	Epidemiological link	Contact with a confirmed case, sick or dead animals, probable cases	Any person who has been in direct or indirect contact (which may mean frequenting the same environment as the suspect or confirmed case, or having been in direct contact with a contact of a confirmed case) with a confirmed case or a suspect case
		Unsafe burial of a probable or confirmed case	
		Unprotected sexual intercourse with a recovered case, contact with sick or dead animals	
7	Respiratory signs	Dyspnoea	Any symptoms associated with damage to the respiratory system
		Cough	

Table 2: The probability of E.V.D. given the 7 factors present in the patient according to each expert's experience.

Expert	1	2	3	4	5	6	7	Sum	N	Average
P(MVE+)	0.6	0.7	0.8	0.8	0.7	0.2	1	4.8	7	0.69
P(MVE-)	0.4	0.3	0.2	0.2	0.3	0.8	0	2.2	7	0.31

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Table 3: The likelihood ratio for the clinical diagnosis of E.V.D. (abaque).

Probability Presence of E.V.D. given the presence of absence of a factor	P (F+/MVE+)										Probability No E.V.D. given the presence of absence of a factor	P (F +/MVE -)										L.H. R	Impact
	Exp1	Exp2	Exp3	Exp4	Exp5	Exp6	Exp7	S	N	M		Exp1	Exp2	Exp3	Exp4	Exp5	Exp6	Exp7	S	N	M		
P(F1 +/MVE +)	1	0.5	0.8	1	0.8	0.8	0.6	5.5	7	0.79	P(F1 +/ MVE -)	0	0.3	0.2	0	0	0.8	0.3	1.6	7	0.23	3.44	+
P(F2 +/MVE +)	0.6	0.7	0.6	0.7	0.7	0.3	0.5	4.1	7	0.59	P(F2 +/ MVE -)	0.3	0.7	0.2	0.3	0.3	0.5	0.4	2.7	7	0.39	1.52	+
P(F3 +/MVE +)	0.7	0.8	0.6	0.7	0.8	0.8	0.8	5.2	7	0.74	P(F3 +/ MVE -)	0.4	0.8	0.4	0.3	0.4	0.8	0.1	3.2	7	0.46	1.63	+
P(F4 +/MVE +)	0.9	0.8	0.5	0.7	0.7	1	0.8	5.4	7	0.77	P(F4 +/ MVE -)	0.5	0.8	0.7	0.3	0.4	0.9	0.1	3.7	7	0.53	1.46	+
P(F5 +/MVE +)	1	0.8	0.7	0.8	0.9	0.8	0.8	5.8	7	0.83	P(F5 +/ MVE -)	1	1	0.2	0.2	0.6	0.9	0.1	4	7	0.57	1.45	+
P(F6 +/MVE +)	1	1	0.8	1	1	1	0.9	6.7	7	0.96	P(F6 +/ MVE -)	0.3	0.3	0.3	0	1	0.3	0.1	2.3	7	0.33	2.91	+
P(F7 +/MVE +)	0.7	0.3	0.6	0.6	0.6	0.4	0.4	3.6	7	0.51	P(F7 +/ MVE -)	0.3	0.5	0.3	0.4	0	0.5	0.5	2.5	7	0.36	1.44	+
	P (F -/MVE +)											P (F -/MVE -)											
P(F1 -/MVE +)	0	0.5	0.2	0	0.2	0.2	0.4	1.5	7	0.21	P(F1 -/ MVE -)	1	0.7	0.8	1	1	0.2	0.7	5.4	7	0.77	0.28	-
P(F2 -/MVE +)	0.4	0.3	0.4	0.3	0.3	0.7	0.5	2.9	7	0.41	P(F2 -/ MVE -)	0.7	0.3	0.8	0.7	0.7	0.5	0.6	4.3	7	0.61	0.67	-
P(F3 -/MVE +)	0.3	0.2	0.4	0.3	0.2	0.2	0.2	1.8	7	0.26	P(F3 -/ MVE -)	0.6	0.2	0.6	0.7	0.6	0.2	0.9	3.8	7	0.54	0.47	-
P(F4 -/MVE +)	0.1	0.2	0.5	0.3	0.3	0	0.2	1.6	7	0.23	P(F4 -/ MVE -)	0.5	0.2	0.3	0.7	0.6	0.1	0.9	3.3	7	0.47	0.48	-
P(F5 -/MVE +)	0	0.2	0.3	0.2	0.1	0.8	0.2	1.8	7	0.26	P(F5 -/ MVE -)	0	0	0.8	0.8	0.4	0.1	0.9	3	7	0.43	0.6	-
P(F6 -/MVE +)	0	0	0.2	0	0	0	0.1	0.3	7	0.04	P(F6 -/ MVE -)	0.7	0.7	0.7	1	0	0.7	0.9	4.7	7	0.67	0.06	-
P(F7 -/MVE +)	0.3	0.7	0.4	0.4	0.4	0.6	0.6	3.4	7	0.49	P(F7 -/ MVE -)	0.7	0.5	0.7	0.6	1	0.5	0.5	4.5	7	0.64	0.76	-

*L.H. R>1, the factor increases the probability of the case being positive for E.V.D.
*L.H. R <1, the factor reduces the probability of the case being positive for E.V.D.
*L.H. R=0, the factor is indifferent, so no conclusion can be drawn in this case.

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The Q.A.P.O. with all the factors present is calculated as follows:

$$QAPO = \frac{P(F_1^+/MVE^+)}{P(F_1^+/MVE^-)} * \frac{P(F_2^+/MVE^+)}{P(F_2^+/MVE^-)} * \frac{P(F_3^+/MVE^+)}{P(F_3^+/MVE^-)} * \frac{P(F_4^+/MVE^+)}{P(F_4^+/MVE^-)} * \frac{P(F_5^+/MVE^+)}{P(F_5^+/MVE^-)} * \frac{P(F_6^+/MVE^+)}{P(F_6^+/MVE^-)} * \frac{P(F_7^+/MVE^+)}{P(F_7^+/MVE^-)} * \frac{P(MVE^+)}{P(MVE^-)}$$

QAPO=RV*QAPRI

$$OAPO = 3.44 * 1.52 * 1.63 * 1.46 * 1.45 * 2.91 * 1.44 * 2.18 = 164.2$$

The Q.A.P.O. with all the factors absent is calculated as follows:

$$QAPO = \frac{P(F_1^-/MVE^+)}{P(F_1^-/MVE^-)} * \frac{P(F_2^-/MVE^+)}{P(F_2^-/MVE^-)} * \frac{P(F_3^-/MVE^+)}{P(F_3^-/MVE^-)} * \frac{P(F_4^-/MVE^+)}{P(F_4^-/MVE^-)} * \frac{P(F_5^-/MVE^+)}{P(F_5^-/MVE^-)} * \frac{P(F_6^-/MVE^+)}{P(F_6^-/MVE^-)} * \frac{P(F_7^-/MVE^+)}{P(F_7^-/MVE^-)} * \frac{P(MVE^+)}{P(MVE^-)}$$

QAPO=RV*QAPRI

$$QAPO = 0{,}28 * 0{,}67 * 0{,}47 * 0{,}48 * 0{,}60 * 0{,}06 * 0{,}76 * 2{,}18 = 0{,}003$$

We can calculate the probability in both cases, as we have already found the Q.A.P.O. with all the factors present and the Q.A.P.O. with all the factors absent.

A. The probability of a positive diagnosis with all the factors present in a patient

$$P = \frac{164{,}2}{1 + 164{,}2} = 0{,}9939 = 99{,}4\%$$

B. The probability of a positive diagnosis with all the factors absent in a patient

$$P = \frac{0{,}003}{1 + 0{,}003} = 0{,}0029 = 0{,}3\%$$

C. The few probabilities of a diagnosis of E.V.D. via the Bayesian approach

The major factors influencing the clinical diagnosis of Ebola are identified on the basis of the calculations in Table 4.

Factors F1 (haemorrhagic signs) and F6 (epidemiological link) are major factors in the positive diagnosis of a patient suspected of having Ebola virus disease. Among these two factors, F6 is the most influential. When it is absent from the model, the probability of a positive diagnosis of a suspected case of E.V.D. decreases significantly.

Internal evaluation of the E.V.D. diagnostic model

The degree of intra- and interexpert agreement for the clinical diagnosis of E.V.D.

The degree of intra- and inter-expert agreement for the clinical diagnosis of Ebola was calculated using Table 5.

Based on the hypothetical cases in the first and second rounds, each expert answered the following question: "Out of 6 cases that you know of with different E.V.D. factors, how many had a positive E.V.D. result?". Next, contingency tables were constructed based on the 0.5 discrimination criterion. In addition, the probability of observed matches and the probability of expected matches had to be calculated to derive the kappa (K) statistic.

Table 4: Some probabilities of a diagnosis of Ebola virus disease via Bayesian methods.

CASE	EVD risk factors	L.H. R	QAPRI	QAPO	Probability of E.V.D.	%
1	F1, F2, F3, F4, F5, F6, F7	75.298	2.18	164.2	0.994	99.4
2	F1, F2, F3, F4, F5, F6	39.508	2.18	86.1	0.989	98.9
3	F1, F2, F3, F4, F5, F7	1.65	2.18	3.6	0.782	78.2
4	F1, F2, F3, F4, F6, F7	31.158	2.18	67.9	0.985	98.5
5	F1, F2, F3, F5, F6, F7	25.015	2.18	54.5	0.982	98.2
6	F1, F2, F4, F5, F6, F7	21.949	2.18	47.8	0.98	98
7	F1, F3, F4, F5, F6, F7	33.442	2.18	72.9	0.986	98.6
8	F2, F3, F4, F5, F6, F7	6.085	2.18	13.3	0.93	93
9	F1, F6	0.703	2.18	1.5	0.605	60.5
10	F2, F3, F4, F5, F7	0.133	2.18	0.3	0.225	22.5
11	F1, F2, F3, F6	5.431	2.18	11.8	0.922	92.2
12	F4, F5, F7	0.017	2.18	0	0.036	3.6
13	F2, F3	0.01	2.18	0	0.021	2.1
14	All factors absent	0.001	2.18	0	0.003	0.3

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Table 5: Intra- and interexpert accreditation for the clinical diagnosis of E.V.D.

Kappa	Intra- and interexpert accreditation for the clinical diagnosis of E.V.D.						
	Expert1	Expert2	Expert3	Expert4	Expert5	Expert6	Expert7
Expert 1	1						
Expert 2	0.13	1					
Expert 3	0.13	1	1				
Expert 4	0.85	0.2	0.2	0.86			
Expert 5	0.21	0.66	0.66	0.31	1		
Expert 6	0.48	0.28	0.28	0.56	0.49	0.41	
Expert 7	0.13	0.73	0.73	0.08	0.74	0.28	0.76

Table 6: The discrimination criterion for diagnosing E.V.D.

We used hypothetical cases and expert consensus for the diagnosis of E.V.D.										
	a	b	c	d	Total	Se	Sp	VPP	VPN	VEG
0,1	42	0	0	0	42	100	-	100	-	100
0,2	42	0	0	0	42	100	-	100	-	100
0,3	31	10	1	0	42	96.9	0	75.6	0	73.8
0,4	25	14	3	0	42	89.3	0	64.1	0	59.5
0,5	22	13	6	1	42	78.6	7.1	62.9	14.3	54.8
0,6	20	4	8	10	42	71.4	71.4	83.3	55.6	71.4
0,7	20	0	5	17	42	80	100	100	77.3	88.1
0,8	19	0	4	19	42	82.6	100	100	82.6	90.5
0,9	9	0	4	29	42	69.2	100	100	87.9	90.5

The results indicated that six out of the seven experts (86%) had perfect agreement or concordance, i.e., K ≥ 0.75 in the experts' responses in the first and second rounds. Among the experts, one showed acceptable agreement, i.e., 0.4 ≤ K ≤ 0.75.

The interexpert agreement yielded a value of 9 (43%) out of 21 agreements, resulting in a kappa value greater than 0.40. Therefore, it was necessary to use expert consensus data to evaluate the Bayesian model. First, we had to determine the discrimination criterion (cut-off point, abbreviated C.O.P.).

The discrimination criterion (cut-off point) for diagnosing E.V.D.

The discrimination criterion for the clinical diagnosis of Ebola is found based on the calculations in Table 6.

Considering the discrimination criterion in Table 6, the sensitivity, specificity, and negative and positive predictive values were high. The highest values of sensitivity, specificity, negative predictive value and positive predictive value were obtained at a discrimination criterion of 0.8, which was thus retained as the cut-off point (Se = 82.6; Sp = 100.0; PPV = 100.0; N.P.V. = 82.6 and VEG = 90.5).

Internal validation of the E.V.D. diagnostic model.

The internal evaluation parameters of the model, that is, Se, Sp, P.P.V., and N.P.V., were calculated from Table 7.

$$S_e = \frac{a}{a+c} * 100 = \frac{19}{19+23} * 100 = 82{,}6\ \%$$

$$S_p = \frac{d}{d+b} * 100 = \frac{19}{0+19} * 100 = 100{,}0\ \%$$

$$P.P.V = \frac{a}{a+b} * 100 = \frac{19}{19+0} * 100 = 100{,}0\ \%$$

$$N.P.V = \frac{d}{c+d} * 100 = \frac{19}{4+19} * 100 = 82{,}6\ \%$$

$$Overall\ efficiency\ value = \frac{a+b}{a+b+c+d} * 100 = \frac{19+19}{19+0+4+19} * 100 = 90{,}5\ \%$$

$$K = \frac{P_o - P_e}{1-P_e} = 0{,}81$$

The internal validity of the M.S.B. was established because all the assessment parameters were relatively high. The degree of agreement is perfect, with a kappa of 0.81.

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Table 7: The confrontation between the Bayesian subjective model and the consensus of experts on hypothetical cases.

M.S.B. (cutoff Point is 0,8)	E.V.D. diagnosis (Hypothetical cases)	Expert consensus (cutoff Point is 0.8)		Total
		MVE+	MVE-	
	MVE+	19	0	19
	MVE-	4	19	23
	Total	23	19	42

Discussion

There is often a degree of uncertainty in clinical decision-making. Clinicians typically make diagnostic decisions based on clinical signs and/or symptoms. The clinical diagnosis from the most experienced clinician is often further confirmed after a laboratory examination.

For E.V.D., clinical epidemiologists determine the classification of a patient as a sus-pected case of Ebola based on clinical signs and symptoms. These clinical epidemiologists are often faced with confusion in the differential diagnosis between malaria and E.V.D.. Only a bi-ological examination in the laboratory can resolve differences of opinion between two epidemi-ological clinicians.

The internal validation of the diagnostic prediction model revealed that the model per-formed very well in detection and prediction. With respect to detection, our model can detect true positive cases at 82.6% (sensitivity) and true negative cases at 100% (specificity), considering all the factors listed by the experts. Our model correctly predicted positive E.V.D. cases at rate of 100% (positive predictive value) and correctly predicted cases negative for E.V.D. at a rate of 82.6% (negative predictive value).

Given the relatively high values of all the evaluation parameters and the kappa coefficient, which demonstrated a high degree of agreement (kappa = 0.81), the model developed herein was internally validated.

The Bayesian model has already proven its performance in other studies. This is the case for the study by Mwokozi et al.7 (2015) on the predictive analysis of factors in the occurrence of stroke among professors at the University of Kinshasa. In this study, the M.S.B. could predict many cases of stroke (16 in total) or no stroke (26 in total) by using the following parameters: Se, Sp, V.P.P., VPN and VEG 7.

Gustafson et al.8 designed a predictive model to detect patients complaining of suicidal desire with the idea of classifying them into two categories—those who were at serious risk of suicide and those who were not. The results obtained were compared with the observed changes in suicide desire and the predictions of psychiatrists8.

Barhayiga et al.9 published a study entitled "Predictive analysis using the Bayesian ap-proach of risk factors of the occurrence of anesthetic accidents and incidents in hospitals in Kinshasa". Therein, the experts developed a list of 188 factors, and the nominal group technique determined 58 factors, which were grouped into 8 independent, mutually exclusive factors to calculate the Q.A.P.R.I., likelihood ratio, Q.A.P.O. and, probabilities of the occurrence of an-aesthetic accidents and incidents (A.I.A.). The a priori probability quotient (Q.A.P.R.I.) was 0.43. The two Q.A.P.O.s were 0.9 for all the present factors and 0.19 for all the absent factors. The performance of the M.S.B. internally from the hypothetical cases was as follows: Se = 94.8% (out of 100 A.A., the model had predicted 94.8%), Sp = 75.0% (out of 100 non-A.A., the model had predicted 75.0%), V.P.P. = 80.4% (out of 100 A.A. predicted by the model 80.4% were truly A.A. (objective cases)) and N.P.V. = 93.1% (out of 100 non-A.A. predicted by the model 93.1% had actually been non-A.A. (objective cases)). In conclusion, the authors confirmed that identifying contributing factors via the Bayesian model could help practitioners take primary preventive measures to reduce the morbidity of anaesthetic accidents in our context9.

Munyanga et al.10 developed a Bayesian model for predicting the success of health zones in the D.R.C. This Bayesian model, compared with the opinions of experts, yielded the following parameters: Se = 98%, Sp = 89%, V.P.P. = 93%, N.P.V. = 96%, and Kappa = 0.87%10. This model was efficient, given that all the parameters were high enough.

The E.V.D. diagnosis prediction model developed herein via the Bayesian approach performed better than other models developed by researchers in another field.

Conclusion

During the present study on the prediction of a clinical diagnosis of E.V.D., Bayesian analysis made it possible to identify the different factors that could influence a confirmed posi-tive diagnosis of a patient suspected of having E.V.D.

Several studies have reported some factors that could be found in a patient with E.V.D. without impacting a positive diagnosis of E.V.D. On the other hand, in the present study, the impact of each predictive factor of a positive diagnosis of E.V.D. was demonstrated in a chart on the basis of the opinions of E.V.D. experts via the Bayesian approach. Although the model was validated internally, it requires external validation with real E.V.D. data.

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experts who agreed to participate in the session to develop this prediction model, despite their busy schedules.

Author contributions

JKK and SM designed the study, performed the experiments, analysed the data and wrote the manuscript. PK, JK, JN, OC, SA, GM, SB and RM performed the experiments and wrote the manuscript. DB, TS, WB, BM, GM, FD, AM, JB, BK, DM, CB, BK and EK performed the ex-periments.

Additional information

Competing interests

The authors declare no competing interests.

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