Data Mining from Knowledge Cases of COVID-19

MARIYA EVTIMOVA-GARDAIR
University Paris 1 Panthéon- Sorbonne, INRIA,
Paris,
FRANCE

Abstract: - A lot of articles were produced during the pandemic of COVID-19 and continue to be produced. The article proposes a system for diagnosis of COVID-19 disease. Also nowadays, the presentation of knowledge and the research for the reasoning algorithms are progressively improving in the domain of Artificial Intelligence. Besides these, distributed reasoning as a part of data mining has become a solution for the increasing everyday data amount. As a result, the paper proposes a case-based non-monotonic reasoner for uncertain and vague COVID-19 information that is appropriate for work with Big Data. Also, a COVID-19 knowledge base model is proposed. The reasoner implements rules for the distribution of the information that gives the possibility to work with Big data. The proposed reasoning algorithm is applied for COVID-19. It shows the implementation of the reasoner into the data mining system and the returned results from the system are evaluated. The results show that the system returns relatively high results concerning the other system for recommendation.

Key-Words: - COVID-19, rule-based reasoning, case-based reasoning, data mining, reasoning, non-monotonic reasoning, jColibri.

Received: May 11, 2023. Revised: December 12, 2023. Accepted: January 9, 2023. Published: February 20, 2024.

1 Introduction

In the effort to respond to the overwhelming need defined by the pandemic of COVID-19 are created many computer-aided applications for diagnosis and recommendation. The recent literature that describes COVID-19 solutions is defined also as the issues that are an object of continuous improvement such as methods for analysis and the poor quality of the data sets, [1]. The reasoning methodologies in intelligent systems can be divided into rule-based reasoning and case- based reasoning. Using rules can define general knowledge and using cases reuse already-defined knowledge in specific situations. Each research technique has its advantages and disadvantages, which have been proven to be mostly complementary. Combining two or more different reasoners and hybrid knowledge representation is a very active research area in artificial intelligence, [2]. The aim is to create a combined formalism that uses the advantages of the methods.

The effectiveness of the different hybrid or integrated approaches has been demonstrated in several areas of application. The effectiveness of these studies is because the rules are complementary in a field of application or solving a problem.

Rule-based systems solve problems from the start while case-based systems use previously stored situations to deal with a similar case. Therefore, the combination of the two approaches is natural and useful. Complementary advantages and disadvantages of both intelligent methods enhance the benefits of their combination. Furthermore, the combination of fuzzy and probability theory proves their possibility when using uncertain and vague information from the query. Those methods are integrated to improve the quality of the searched information in Big Data which is particularly important when performing diagnosis for COVID-19. Conversely, this work focuses on the distributed non-monotonic reasoning methodology. It could be defined the following technical contribution to the study:

1) Definition and creation of COVID-19 case-based ontology for feature extraction and mapping from suspected cases of COVID-19.
2) Proposal of a novel mathematical model for semantic-based and feature-based case similarity computation.
3) Incorporation of the proposed reasoning model into an improved CBR (Case-Based Reasoning) framework.
4) Implementation of CBR framework which allows for the detection or classification of suspected cases of COVID-19 as either positive or negative.

The content of the article is organized into seven sections. The first section performs the introduction of the article. The second section describes the related work concerning reasoning over COVID-19. The third section represents the knowledge base model that is used for the reasoner. The fourth section of the article represents the reasoning model. The fifth section describes the proposed COVID-19 data mining system and the implementation of the proposed Big data reasoning algorithm. Section 6 proposes the evaluation of the system. In the end, the study concluded with section 7.

2 Related work

The research activity in reasoning and explanation as a part of artificial intelligence has been started for several decades. Moreover, using the classic variant of propositional logic seems to be not an appropriate choice when doing reasoning tasks in real applications because of the presence of conflicting and inconsistent information. The explanation of this is with the monotonicity property that uses consequence relation when implementing formula into the theory but as a result, is not reaching a reduction of the consequence set.

Generally, monotonicity relies on the fact that learning a new set of knowledge is not able to reduce the already known set of knowledge. Also, it can be defined that when applying a standard monotonic reasoning a conclusion that respect package of premises is still valid if another package premises is added, [3]. But that property cannot permit the removal of well-known knowledge as a contradiction of what can be observed in human-like reasoning that can be classified as non-monotonic. As a definition non-monotonic reasoning represents the possibility of a conclusion with a set of premises to be removed to update the existing information.

As a consequence of this, non-monotonic reasoning can have true premises but not corresponding conclusions. Regarding monotonic reasoning can be defined that when premises are true the conclusions necessarily follow them. The non-monotonicity property supports that the claim can specify partial premises but when an exception arises it can be withdrawn.

Also, including new premises can be associated with retracting described as non-monotonicity, rather than implementing new conclusions described as monotonicity). Since the beginning of the COVID-19 pandemic, many articles have been produced to propose a solution to the fight against COVID-19. Article, [4], describes the epistemological problem of induction in COVID-19. Another article, [5], describes the uncertainty when making decisions during the COVID-19 pandemic. To analyze the COVID-19 data in Mexico is implemented a non-monotonic behavior of the real data, [6]. Paper, [7], proposes an investigation of the spread of COVID-19 by countries that use non-monotonous relationships. Reasoning over COVID-19 ontology is described in [8]. An approach of fuzzy case-based reasoning that evaluates COVID-19 patients is described, [9]. Another technique used for COVID-19 are [10], [11]. Some articles are more general, [12], which also describe the benefits of using artificial intelligence for searching COVID-19 data.

3 Representation of Knowledge Base Model that was used for the Reasoner

A brief description of the knowledge base schema that was used for the system is defined in Figure 1. In the schema are defined the COVID-19 symptoms, [13]. The symptoms for COVID-19 defined in [13], and reused in this research are Cough, Fever, Anosmia, Pneumonia, Acute respiratory distress syndrome(ARDS), Organ failure, Dyspnea, Nausea and vomiting, Headache, Diarrhea, Respiratory tract infections.

Shortness of breath, Rhinorrhea, Gastrointestinal symptoms, Chest pain/tightness, Abdominal pain, Muscle pain, Loss of appetite, PaO2, SaO, Loss of smell, Heart rate, Systolic pressure, Diastolic pressure, Fatigue, Septic shock, Sore throat, pH, Temperature, Pharyngeal pain. The data is taken from the Bulgarian hospital St. George, then they are adapted in a case-based format that is suitable for the platform Colibri.

The proposed case-based knowledge data model is compatible with CBROnto. Rules as well as additional classes are not represented in the knowledge model. As presented in Figure 1 CBR INDEX includes all the features of the precedent, CBRCASE includes the individual capabilities of the precedent, and HAS-COMPONENT the two parts of the precedent diagnosis and precedent description. In the precedent-based model, precedents are represented as exemplar concepts and their attributes are represented as semantic relations and properties. The values that link attributes can be taken as precedents defined within the same domain knowledge model.

DOI: 10.37394/23209.2024.21.10

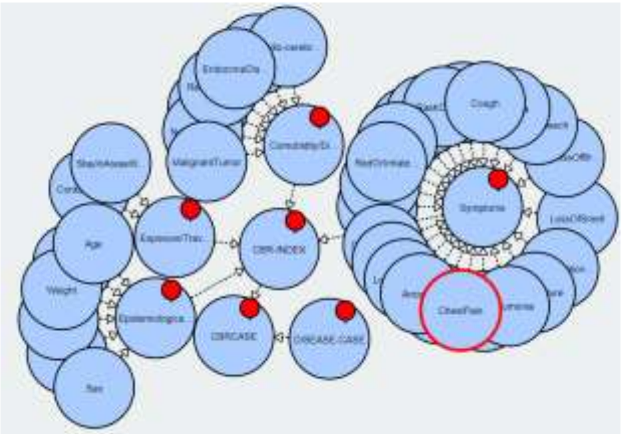

Fig. 1: Case-based knowledge base schema

The schema represented in Figure 2 provides the mechanism for retrieving data from the knowledge base. To personalize and precise the returned information from the system, it is defined as a user profile. The user profile includes the personalized information from the user that is used during retrieval with the current symptoms provided in the system to perform the diagnostic and return appropriate results. The COVID-19 information was used from, [13].

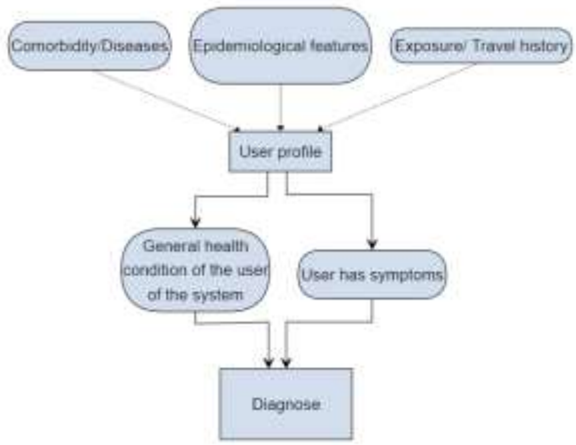

Fig. 2: Representation of the user profile for personalization of the result

The schema provides the mechanism for retrieving data from the knowledge base. The user profile gives the possibility for each user of the system to add their specific information that improves the proposed results from the system.

4 Representation of Non-Monotonic Reasoning Model

This reasoner is appropriate to use with the described knowledge base above. Another interesting research related to the knowledge base for drugs for COVID-19 is described, [14]. The proposed reasoning algorithm uses a case-based reasoning theory and also the rule-based reasoning theory. The combination of the two algorithms is defined to propose a quality reasoning solution for Big Data. The first phase of the algorithm includes the implementation of rules-based reasoning. To meet the Big Data challenge the proposed reaso ner implements distributed reasoning. To realize this complexity, several defined rules and data are distributed among separate peers. Using a selection of a Big set of data inevitably leads to the presence of uncertainty, because of the incomplete information. For example, if it is necessary to give a diagnosis of disease using a query that contains in the query text such as fever and chest pain. But that can be used for all COVID-19 diseases or it can be considered only the COVID-19 disease and then to conclude with a certain degree of uncertainty.

This step can increase the matching degree, as the step is characterized by incompleteness and uncertainty. Two stages can be defined concerning this:
1) preparation of the separation of the data
2) definition of data distribution

The basic problem observed in stages 1 and 2 is the presence of certain events with certain rules that cannot be concluded if they are not related. The distribution of the rules and cases is strictly defined. So that the expressions that are connected must if it is possible to coexist in the same peer.

The distribution is defined so that every peer is linked with a set of rules and a set of cases.

Each peer has defined entities:
1) basic rules to the concept that present a class of strict and conditional restrictions
2) concept of the case that presents a class of cases
3) concept of the peer that presents a class of peers

The basic rules have the form: **Rule**: (**m** — **n**[**md**]), means that if **n** holds then **m** normally holds with a matching degree **md**. The cases have the form: Case: (**c—T[md]**), which means that the case is true with matching degree **md**, where the activation weight of the rule represents the matching degree, i.e. degree of belief. As it is described in [15], [16], the disjunctive belief reasoning is implemented. This equivalence serves as a way of using probabilistic knowledge bases to represent uncertain and vague concepts. Each concept could be associated with another concept, indicating that there is a correlation. This is presented with a key value:

• if **m** then **n** with activation weight **A** and matching degree md

• **m** is true with activation weight **A** and matching degree **md**

The role of the key value includes a general description of the rules and a description of the cases. The general description

---

Algorithm 1 Algorithm implementing correlation factor

1: Determination of the number of peers equal to the number of key values
2: For each concept is needed to connect the concept with the peer that has the same number as the key value of the case
3: Finding a conclusion about cases and rules for each peer of the rules describes rules, which can only be used when there is a specific case. The description of the cases describes cases that are derived from the same result in the same general rules i.e. "If COVID-19 disease has fever with factor 1", then this is true for all COVID-19 type diseases, as a rule, fever is common. This means that the procedure for conclusions needs to be applied only once for each case. Once the key value is determined for each concept, the correlation of the two concepts is defined as follows: If c1 and c2 are the concepts, then they are related when the matching degree has the same value.

So the first stage in the method is to distribute the cases and the rules between the peers according to the value of the matching degree. For example, if there is a rule of COVID-19 disease that affect different parts of the body, then the key is the frequency of occurrence of a disease, and therefore the COVID-19 cases can be allocated to peers depending on the category of the symptoms that could separate the diseases, i.e. abdominal symptoms, cardiovascular system symptom, digestive system symptom, head and neck symptom, musculosceleton system symptom, nervous system symptom, neurological and physiological symptom, nutrition metabolism and development system symptom, reproductive system symptom, respiratory system and chest symptom, skin and integumentary tissue symptom, urinary system symptom, hemic and immune system. Description of the algorithm with correlation factor, [15], [17], Figure 3 presents the proposed model for distributed reasoning. The key value also determines the number of used peers.

The number of used peers is equal to the number of used key values. After determining each peer, each peer contains the number of cases and rules. Then is applied the algorithm for reasoning. This process runs independently in each peer without taking into account other peers, [18]. The problem could occur in situations where two rules have the same conclusion with different matching degree values. For example, if there are two rules COVID-19 diseases have fever with factor 0.5 and COVID-19 disease always have chest pain, then the second rule should be applied instead of the first.
Furthermore, these conflicts can arise in situations where there are exceptional classes (such as heart disease) and special rules, so extra classes are treated as opposed to the total class. The algorithm for the reasoning of each peer is presented below:
Reducing the facts serves as a way to stop running rules with low priority, so that if a rule that starts has priority 2, then by reducing the fact that causes running, the rule with priority 1 is not going to be implemented. Finally, a solution for the most similar case is retrieved and proposed to the user.

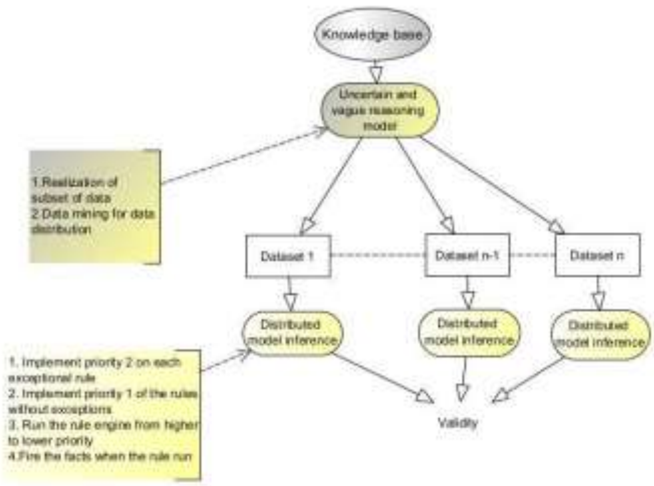

Fig. 3: Representation of algorithm for distributed reasoning

DOI: 10.37394/23209.2024.21.10

Finally, a solution for the most similar case is retrieved and proposed to the user.

Algorithm 2 Algorithm that is executed to each peer

1: Implement priority 2 on each exceptional rule
2:Implement priority 1 of the rules without exceptions
3: Run the rule engine from higher to lower priority
4: Cancellation of the facts when the rule run
for the most similar case is retrieved and proposed to the user.

This algorithm for reasoning is suitable for working with Big Data and can handle vague and uncertain data that include the belief-defined case to be a conclusion. The schema of the reasoner construction is shown in Figure 3. The reasoning algorithm is created using SWRL rules.

5 Description of COVID-19 Data Mining System with the Proposed Reasoning Algorithm

The developed application model with the proposed reasoner is shown in Figure 4 as the application is divided into three layers and each layer has a specific task. For the practical realization of the model is used the Java library jColibri, [19] and Jess. Furthermore, case-based reasoning is used also in [20], which is an article related to COVID-19.

The primary layer maintains the communication of the knowledge graph with cases. Then the application layer contains the retrieved data from the cases. This layer is case-based and is very important for the application. The interface layer can accept the request from the user application and return the nearest event. In the application, only the steps for presentation and searching. The model does not include an adaptation of the cases and their storage, which describe clearly the structure of the proposed reasoner. The reasoner is presented in two steps. The first step is reasoning with uncertain and vague information.

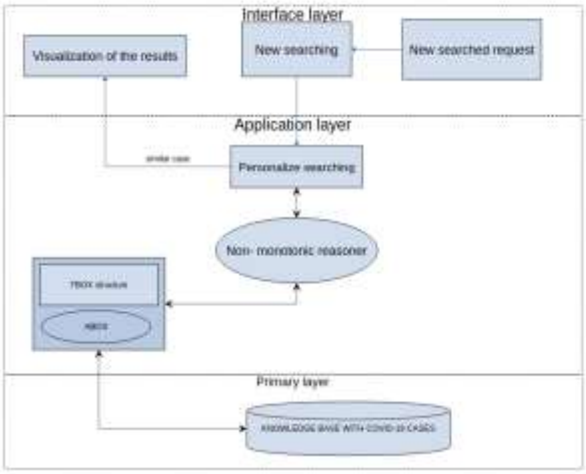

Fig. 4: Personalized data mining system in layered model

6 Evaluation of the Results from the System

Basically for estimation of the results of the search system are accepted three parameters Precision, Recall, and F-Measure. The aim of the semantic search within COVID-19 knowledge base is to increase precision and recall, where in Figure 5 present the formulas.

$$Precision = \frac{Numberofrelevantretrievedresults}{Numberofretrieveddocuments} \quad (1)$$

$$Recall = \frac{Numberofretrieveddocuments}{Numberofrelevantdocuments} \quad (2)$$

$$F - measure = \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

Fig. 5: Formulas for precision, recall and F-measure

For the evaluation of the system, 223 user requests for COVID-19 were taken from various internet sources. The data is separated into eleven categories concerning the symptoms that affect different parts of the body: Head and neck symptoms, Musculosceleton system symptom, Nervous system symptoms, Respiratory system and chest symptom, Skin and integumentary tissue symptom. Then the proposed system is evaluated by an expert and the results returned from the system and the expert are compared. The proposed system analysis does not account for the results when both the expert and the system give different results for a given disease, so the negative predicted value parameter cannot be estimated. The system is making general diagnostics for COVID-19 disease.

The system is one shot i.e. returns a single result. Figure 6 represents the evaluation of the system concerning the Precision.

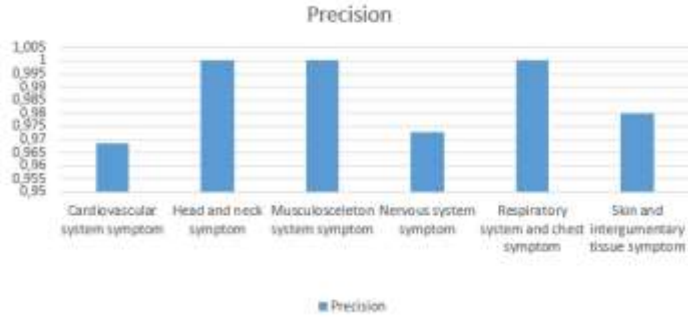

Fig. 6: Precision of the system

Figure 7 presents the evaluation of the system concerning the Recall.

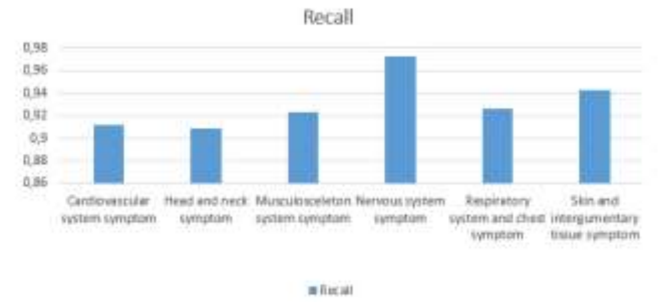

Fig. 7: Recall of the system

Figure 8 shows the F-measure of the system separated into the categories of the system. It calculates the accuracy of the system with medical information about COVID-19 diseases.

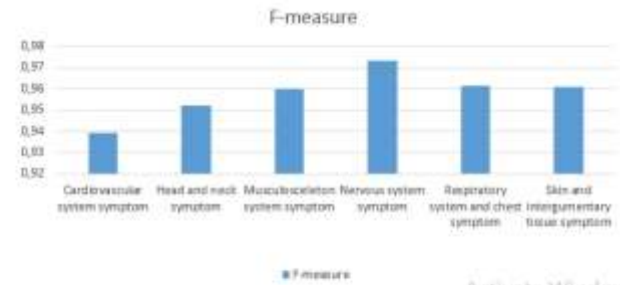

Fig. 8: F- measure of the system

The precision is defined as 99% and the recall as 93% that gives the quality of the system returned results, [21], [22], [23], [24]. Figure 9 represents the analysis of different COVID-19 applications defined in the literature concerning their evaluation results. The results from the analysis defined in Figure 9 show that the proposed system has relatively high results in comparison with the other systems. The system uses Iris prediction cost algorithm for the calculation of the accuracy.

Artificial Intelligence algorithm used	Aim of the research	Precision (%)	Recall (%)	F-measure (%)	Accuracy (%)
Improved metaheuristic algorithm with the advantages of accurate solution method(ICHIO)	COVID-19 detection CBC using machine learning techniques	95.48	-	-	-
ResNet model with the location-attention mechanism	A Deep Learning System to Screen Novel Coronavirus Disease 2019 Pneumonia	75.8	77.26	76.43	79.4
ResNet model	A Deep Learning System to Screen Novel Coronavirus Disease 2019 Pneumonia	74.3	75.8	75	78.5
Machine learning algorithm	Increase COVID-19 inpatient diagnostic capacity	76	-	-	-
Machine learning neural Network based model	A Framework for Pandemic Prediction Using Big Data Analytics	98	98	100	99
Machine learning algorithm Adaboost	Described in analysis for comparison	98	98	99	95
Machine learning algorithm KNN	Described in analysis for comparison	97	97	99	96
Machine learning algorithm Logestic Regression	Described in analysis for comparison	96	97	98	94
Machine learning algorithm Naive Bayes	Described in analysis for comparison	97	97	99	95
Machine learning algorithm Linear SVM	Described in analysis for comparison	98	98	99	97
The proposed case and rule based data mining algorithm	Early diagnostic of Covid 19 based on cases	99	93	96	95,5

Fig. 9: Representation of comparative analysis

The accuracy of the system is defined as 95.5%, [25]. The algorithm is a part of the Colibri framework that also provides tools for testing.

After evaluation of the system, the results show that the system has relatively high quality concerning the other systems.

The analysis methods described in [26], are used to evaluate the system as suitable for Big Data. As a conclusion from the analysis of [27], is defined that speed is crucial for Big Data systems. A computer with the following system configuration is used to test the system: Intel Core i9-13980HX, 32 Go RAM. The results are described in Table 1.

Table 1. Comparative results

	Using case-based algorithm not adapted to work with Big Data	Using the proposed case-based algorithm that uses rules and is adapted for Big data
Time to respond	7524ms	6123ms

The results from Table 1 show that the proposed algorithm that is adapted to work with Big Data is faster and has a smaller time to respond than the algorithm not adapted to work with Big Data.

The total time for searching is bigger when using a standard case-based algorithm that is available in jColibli than the proposed algorithm that is adapted for working with Big Data.

Because the standard algorithm proposed by jColibri does not distribute the data to peers before searching the information and then indexing the results. For the creation of the system, the Colibri framework is available on the internet, [25]. This software provides easy prototyping functionality and contains different searching algorithms and tools for testing. Furthermore, the Colibri framework is a free case-based framework that makes it easily accessible and usable.

7 Conclusion

A reasoning algorithm that is proposed combines case-based and rule-based reasoning. It can be defined as a case-based non-monotonic reasoner that is suitable for vague and uncertain information and can work with Big Data. The proposed non-monotonic reasoning algorithm uses disjunctive belief logic that is adapted to work with COVID-19 data. This algorithm is adapted to be case-based and uses the experience from the previous cases and improve the results from the system. With the combination of the cases, the algorithm also uses rules to provide the possibility to perform distributed searching and work with Big Data. Also, it is proposed a case-based knowledge base model for COVID-19 hospital data. The proposed reasoner is implemented into a personalized COVID-19 system that gives quality results to the user.

References:

[1] Xingyi Yang, Xuehai He, Jinyu Zhao, Yichen Zhang, Shanghang Zhang, Pengtao Xie. *Covid-ct-dataset: a ct scan dataset about COVID-19*. arXiv preprint arXiv:2003.13865, 2020,vol. 490, no 10.48550.

[2] Albahri, Ahmed Shihab, Hamid, Rula A., Alwan, Jwan K., et al. Role of biological data mining and machine learning techniques in detecting and diagnosing the novel coronavirus (COVID-19): a systematic review.*Journal of Medical Systems*, 2020, vol. 44, p. 1-11.

[3] Longo, Luca, Rizzo, Lucas, Dondio, Pierpaolo. Examining the modeling capabilities of defeasible argumentation and non-monotonic fuzzy reasoning. *Knowledge-Based Systems*, 2021, vol. 211, p. 106514.

[4] Vega, Carlos. From Hume to Wuhan: an epistemological journey on the problem of induction in COVID-19 machine learning models and its impact upon medical research. *IEEE Access*, 2021, vol. 9, p. 97243- 97250.

[5] Stan, Sergiu Octavian, Treapat, Mihai Laurent, iu, et Draganescu, Corina Elena. Decisions under uncertainty in the Covid-19 era. *Strategica: Preparing for Tomorrow, Today*, p.731-742, 2020.

[6] Aguilar- Madera, Carlos G., Espinosa-Raredes, Gilberto, Herrera- Hernandez, E. C., et al. The spreading of Covid-19 in Mexico: A diffusional approach. *Results in Physics*, 2021, vol. 27, p. 104557.

[7] Gonzalez-Val Rafael, Sanz-Gracia, Fernando. Urbanization and COVID-19 incidence: A cross-country investigation. *Papers in Regional Science*, 2022, vol. 101, no 2, p. 399-415.

[8] Groza, Adrian. *Detecting fake news for the new coronavirus by reasoning on the Covid-19 ontology*. arXiv preprint arXiv:2004.12330, 2020.

[9] Ahmed Faisal, Hossain Mohammad Shahadat, Islam Raihan Ul, Karl Andersson. An evolutionary belief rule-based clinical decision support system to predict COVID-19 severity under uncertainty. *Applied Sciences*, 2021, vol. 11, no 13, p. 5810.

[10] Cai, Junzhe, Revesz, Peter Z. A Novel Spatiotemporal Method for Predicting Covid-19 Cases. WSEAS *Transactions on Mathematics*, 2021, 20: 300-311, https://doi.org/10.37394/23206.2021.20.31.

[11] Liu, Chenglian; Chen, Sonia CI. Study of COVID-19 Monitoring System Based on Block Chain and Anonymity Techniques. *WSEAS Transactions on Mathematics*, 2022, vol.21, p.635-640, https://doi.org/10.37394/23206.2022.21.74.

[12] Vaishya, Raju, Javaid, Mohd, Khan, Ibrahim Haleem, et al. Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, 2020, vol. 14, no 4, p. 337-339.

[13] Oyelade, Olaide N. et Ezugwu, Absalom E. A case-based reasoning framework for early detection and diagnosis of novel coronavirus. *Informatics in Medicine Unlocked*, 2020, vol. 20, p. 100395.

[14] Khan, Junaed Younus, Khondaker, Md Tawkat Islam, Hoque, Iram Tazim, et al. Toward preparing a knowledge base to explore potential drugs and biomedical entities related to COVID-19: automated computational approach. *JMIR medical informatics*, 2020, vol. 8, no 11, p. 21648.

[15] Belle, Vaishak. Toward Robots That Reason: Logic, *Probability & Causal Laws*. Springer, 2023.

[16] Fu, Yang-Geng, Fang, Geng-Chao, Liu, Yong-Yu, et al. Disjunctive belief rule-based reasoning for decision making with incomplete information. *Information Sciences*, 2023, vol. 625, p. 49-64.

[17] Hariri, Reihaneh H., Fredericks, Erik M., et Bowers, Kate M. Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, 2019, vol. 6, no 1, p. 1-16.

[18] Insaurralde, Carlos C., Blasch, Erik P., Costa, Paulo CG, et al. Uncertainty-driven ontology for decision support system in air transport. *Electronics*, 2022, vol. 11, no 3, p. 362.

[19] Alazzam, Malik Bader, Tayyib, Nahla, Alshawwa, Samar Zuhair, et al. Nursing care systematization with case-based reasoning and artificial intelligence. *Journal of Healthcare Engineering*, 2022, vol. 2022.

[20] Nurgraheni, Murien, SARI, Irma Permata, et al. A Case-Based Reasoning for Detection Coronavirus (Covid-19) Using Cosine Similarity. *In: Conference on Broad Exposure to Science and Technology 2021 (BEST 2021). Atlantis Press*, 2022. p. 178-183.

[21] Gao, Chengcheng, Zhang, Rui, Chen, Xicheng, et al. Integrating Internet multi source big data to predict the occurrence and development of COVID-19 cryptic transmission. *NPJ Digital Medicine*, 2022, vol. 5, no 1, p. 161.

[22] Xu, Xiaowei, Jiang, Xiangao, Ma, Chunlian, et al. A deep learning system to screen novel coronavirus disease 2019 pneumonia. *Engineering*, 2020, vol. 6, no 10, p. 1122-1129.

[23] Goodman- Meza, David, Rudas, Akos, Chiang, Jeffrey N., et al. A machine learning algorithm to increase COVID-19 inpatient diagnostic capacity. *Plos one*, 2020, vol. 15, no 9, p. e0239474.

[24] Ahmed, Imran, Ahmad, Misbah, Jeon, Gwanggil, et al. A framework for pandemic prediction using big data analytics. *Big Data Research*, 2021, vol. 25, p. 100190.

[25] Ma, Li, Tan, Tieniu, Wang, Yunhong, et al. Efficient iris recognition by characterizing key local variations. *IEEE Transactions on Image processing*, 2004, vol. 13, no 6, p. 739-750.

[26] Novitsky, A. V. The concept and evaluating of big data quality in the semantic environment. *Problems in Programming*, 2022, no 3- 4, p. 260-270.

[27] Recio- Garcia, Juan A., Diaz- Agudo, Belen, et Gonzalez- Calero, ‘Pedro A. The COLIBRI platform: tools, features and working examples. *Successful Case-based Reasoning Applications-2*, 2014, p. 55-85.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.