



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 website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



Research article

Application of intelligence-based computational techniques for classification and early differential diagnosis of COVID-19 disease

Boluwaji A. Akinnuwesi^{a,*}, Stephen G. Fashoto^a, Elliot Mbunge^a, Adedoyin Odumabo^b,
Andile S. Metfula^a, Petros Mashwama^a, Faith-Michael Uzoka^c, Oluvide Owolabi^d,
Moses Okpeku^e, Oluwaseun O. Amusa^f

^a Department of Computer Science, Faculty of Science and Engineering, University of Eswatini, (Formerly University of Swaziland), Kwaluseni M201, Manzini, Eswatini, Swaziland

^b Department of Computer Science, Faculty of Science, Lagos State University, Ojo, Lagos State, 102105, Nigeria

^c Department of Computer Science and Information Systems, Mount Royal University, Calgary, Alberta, T3E6K6, Canada

^d Department of Computer Science, University of Abuja, 900105, Nigeria

^e Department of Genetics, University of KwaZulu-Natal, 4041, South Africa

^f Department of English Studies, Faculty of Arts, Adekunle Ajasin University, Akungba-Akoko, Ondo State, 342111, Nigeria

ARTICLE INFO

Keywords:

COVID-19
Coronavirus
Machine Learning
Intelligent classifier
Early differential diagnosis
Deep Learning

ABSTRACT

Clinical methods are used for diagnosing COVID-19 infected patients, but reports posit that, several people who were initially tested positive of COVID-19, and who had some underlying diseases, turned out having negative results after further tests. Therefore, the performance of clinical methods is not always guaranteed. Moreover, chest X-ray image data of COVID-19 infected patients are mostly used in the computational models for COVID-19 diagnosis, while the use of common symptoms, such as fever, cough, fatigue, muscle aches, headache, etc. in computational models is not yet reported. In this study, we employed seven classification algorithms to empirically test and verify their efficacy when applied to diagnose COVID-19 using the aforementioned symptoms. We experimented with Logistic Regression (LR), Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Multilayer Perceptron (MLP), Fuzzy Cognitive Map (FCM) and Deep Neural Network (DNN) algorithms. The techniques were subjected to random undersampling and oversampling. Our results showed that with class imbalance, MLP and DNN outperform others. However, without class imbalance, MLP, FCM and DNN outperform others with the use of random undersampling, but DNN has the best performance by utilizing random oversampling. This study identified MLP, FCM and DNN as better classifiers over LR, NB, DT and SVM, so that healthcare software system developers can adopt them to develop intelligence-based expert systems which both medical personnel and patients can use for differential diagnosis of COVID-19 based on the aforementioned symptoms. However, the test of performance must not be limited to the traditional performance metrics.

1. Introduction

The weekly epidemiological reports on COVID-19 from the World Health Organization (WHO) shows that COVID-19's confirmed cumulative cases are above 240 million with over 4.9 million deaths, as of October 23, 2021, globally (World Health Organization, 2020a). New cases are always reported due to the advent of different SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) variants despite the ongoing vaccination programme across several countries.

SARS-CoV-2 variants, such as Cluster 5, SARS-CoV-2 VOC 202012/01, 501Y.V2, and P.1, have been reported in countries, such as Denmark, the United Kingdom, Brazil, Nigeria, and South Africa. There are possibilities that the variants could weaken the strength of body immune system that is built naturally or due to vaccination and hence reduce neutralization of the effects of the virus in human (World Health Organization, 2020a, 2020b).

The ongoing and prolonged high rates of new infections of SARS-CoV-2, vis-à-vis the occurrences of different variants of SARS-CoV-2, has

Peer review under responsibility of Xi'an Jiaotong University.

* Corresponding author.

E-mail address: bakinnuwesi@uniswa.sz (B.A. Akinnuwesi).

<https://doi.org/10.1016/j.dsm.2021.12.001>

Received 3 August 2021; Received in revised form 29 November 2021; Accepted 6 December 2021

Available online 9 December 2021

2666-7649/© 2021 Xi'an Jiaotong University. Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

continued to strain the government, private organizations and the healthcare systems in all countries. SARS-CoV-2 is said to be ranked number 11 among the deadliest viruses in the world, with a mortality rate of 2.3% (Anne, 2020). These numbers call for serious concerns in the tackling of SARS-CoV-2 and its variants. This situation is worrisome to medical practitioners and the government. Therefore, several public healthcare and social measures are designed to ensure the adequate tackling of the disease in the forms of compulsory face masking, social distancing, contact tracing, temperature check, minimizing social gathering and sales/consumption of alcohol, and provision of vaccines. However, these measures are negatively influenced by factors, such as privacy, data security, freedom of movement and socializing, lack of IT infrastructure, insufficient IT skill, low literacy, and ease of use (Mbunge et al., 2021). These factors influence the decisions of the populace in terms of embracing and complying fully with the government regulations in the tackling of COVID-19 and further influence the spread of the disease, so there is a need to increase the diagnostic capacity and systematic sequencing of SARS-CoV-2. As a result, many clinical methods have been developed to diagnose SARS-CoV-2. However, there have been reports on false-negative rates that ranged from 5% to 40% (Arevalo-Rodriguez et al., 2020; Long et al., 2020; Weissleder et al., 2020).

Studies conducted in China and Singapore reported a few cases of false-negative results to the tune of 29% and 11%, respectively (Fang et al., 2020; Lee et al., 2020). This implies that the clinical methods do not guarantee the accurate diagnosis or classification of COVID-19 and it could be attributed to the type and quality of the specimen obtained, the duration of illness at the time of testing, and the specific assay. Thus, the need arises for scientists to complement the clinical diagnostic methods with computational intelligence methods in order to ensure near to 100% accurate diagnosis and classification.

In addition, COVID-19 and other diseases, such as Malaria, HIV/AIDS, Tuberculosis, Flu and Pneumonia have similar symptoms and this makes the differential diagnosis of COVID-19 at the early stage inevitable, particularly when the infection is very mild and it cannot be established whether the infection is that of Malaria, HIV/AIDS, Tuberculosis, Flu or Pneumonia. Few studies have reported the differential diagnosis of COVID-19 using chest Computed Tomography (chest CT), a medical imaging technique and some of the studies were presented in Long et al. (2020), Murthy et al. (2020), Zeng et al. (2020) and Zuo (2020). We deduced that the computational models presented in the studies focused more on the use of chest X-ray images but not on other regular symptoms, such as, fever or chills, cough, shortness of breath or difficulty breathing, fatigue, muscle or body aches, headache, loss of taste or smell, sore throat, congestion or runny nose, nausea or vomiting, and diarrhea. Moreover, the models are not suitable for the early diagnosis when the symptoms presented are still very mild and chest CT will not be able to show a convincing result in the X-ray images of the lungs and the cardiovascular system. No study known to the authors has used the aforementioned regular symptoms for the development of intelligence-based systems for early differential diagnosis of COVID-19 using classification algorithms of soft computing, machine learning, deep learning, expert system, and Decision Support System (DSS) using non-image-based dataset of COVID-19 infected patients. However, chest X-ray image data of COVID-19 infected patients are mostly used for diagnosis using deep learning algorithm such as Convolutional Neural Network (CNN).

Therefore, we were motivated to carry out an experimental study of the various intelligence-based classifiers that could be applied in early differential diagnosis of COVID-19 disease by considering the aforementioned regular symptoms and using non-image datasets of the symptoms. Our specific objective is to use the available COVID-19 non-image diagnostic dataset to test the performance of the intelligence-based classifiers, i.e., Fuzzy Cognitive Map (FCM), Support Vector Machine (SVM), Logistic Regression (LR), Multilayer Perceptron (MLP), Naïve Bayes (NB), Decision Tree (DT) and Deep Neural Network (DNN) in terms of accuracy, F-measure, recall, precision, balanced accuracy, Mathews Correlation Coefficient (MCC) and Bookmaker informedness (BM). The

goal is to identify the classifier(s) with the best performance in early differential diagnosis of COVID-19. This paves way for future work in this area to develop diagnostic systems that could apply the best performing classifier(s) for early differential diagnosis of COVID-19 using the aforementioned regular symptoms. In the light of this, we have the following research questions (RQ):

- a. **RQ-1:** What are the classifiers that are most appropriate for the differential diagnosis of COVID-19?
- b. **RQ-2:** What is the performance of each of the classifiers identified in (a) above in terms of the accuracy, precision, recall, F-measure, Mathews Correlation Coefficient, balanced accuracy, and Bookmaker informedness?

This paper contributes to the existing literature by presenting the behaviours of the listed classifiers when applied for COVID-19 diagnosis using non-image based COVID-19 datasets on the regular symptoms (e.g., fever, headache, vomiting, diarrhea, etc.) and this is not yet reported in literature at the time of this report. Earlier studies focus more on image-based chest X-ray data of COVID-19 patients for diagnosis and the most used classifier is DNN.

The rest of the paper is organized as follows: Section 2 presents the overview of clinical methods that have been used for diagnosing COVID-19, a detailed discussion on differential diagnosis and a review of related works on the differential diagnosis of COVID-19 disease. The strengths and weaknesses of the diagnostic methods are presented. Section 3 presents materials and methods. Results and discussion are presented in Section 4 wherein the detailed discussion and analysis of the aforementioned intelligence-based techniques are done. The conclusion and managerial implication are presented in Section 5.

2. Literature review

Several clinical diagnostic methods have been developed for COVID-19. However, the use of intelligence-based computational methods to tackle COVID-19 cannot be underestimated. It will be very helpful to complement the clinical diagnostic methods with other intelligence-based computational methods in order to increase the balanced accuracy, BM and MCC. This section presents a brief description of differential diagnosis and the qualitative features of the clinical and computational methods that have been used for COVID-19 diagnosis vis-à-vis their limitations in the current time.

2.1. Differential diagnosis

Differential diagnosis is the defined process that helps to differentiate between diseases with similar symptoms and risk factors. It is a systematic diagnosis process carried out on patients with the view to accurately diagnose a disease that shares the same symptoms with other related diseases and also survives under the same conditions (Mann, 1990; Sand, 2015; Uzoka et al., 2016). Differential diagnosis is required because rarely do physicians diagnose a disease with certainty, directly from the presentation alone, especially in cases where the symptoms presented relate to many diseases (Jain, 2017). For example, diseases including HIV/AIDS, Malaria, Flu, Tuberculosis, COVID-19, Ebola Virus Disease (EVD), Cholera, etc. have some similar symptoms. Thus, when patients exhibit one or more of these symptoms, the physicians need to subject them to a differential diagnostic process with the view to establishing the actual disease in the multiple related diseases.

The differential diagnosis process entails weighing the probability of a disease against the probabilities of other related diseases that possibly account for patients' illness. Differential diagnosis has shown its usefulness in many instances in medicine. It has helped save lives that would have been otherwise lost and we have seen many lives nearly lost because of the ignorance of differential diagnosis. A notable case of a life almost lost due to the ignorance of differential diagnosis is that of a little girl by

the name of Isabel as reported in Rutledge (2017). The girl who was diagnosed with chickenpox was misdiagnosed by her family doctor, leading to wrong treatment, having her spend about 60 days in the hospital and almost losing her life for multiple organ failures and cardiac arrest. All is from a misdiagnosis that could have been otherwise avoided with differential diagnosis to attain the proper diagnosis at the first time. Though differential diagnosis consumes time, its help in making sure doctors get the right diagnosis and treatment is undeniable.

2.2. Clinical methods for COVID-19 diagnosis

The cause of COVID-19 is attributed to SARS-CoV-2. Many health complications that are related to the virus have been established in the literature to include the following-failure of respiratory system, complications in cardiac and cardiovascular system, inflammatory complications, thromboembolic diseases, neurological disorders, and multi-organ dysfunctions (Alpdagtas et al., 2020; McIntosh, 2020). Researchers are working tirelessly on various clinical methods of diagnosing and treating COVID-19, in order to reduce cases of identified health complications. Thus, some of the clinical diagnostic methods employed are chest radiographs, chest CT, point-of-care lung ultrasonography, clinical suspicion, Nucleic Acid Amplification Tests (NAATs), point-of-care NAATs (Caliendo and Hanson, 2021).

CT diagnosis is generally used for auxiliary diagnosis of the SARS-CoV-2 and the diagnosis is confirmed by positive results of a nucleic acid amplification test (NAAT) of the respiratory tract or blood specimens using an rRT-PCR (reverse real-time PCR assay) reaction (Dai et al., 2020). However, it was reported that the rRT-PCR method of diagnosis has limitations. The implication is that when the viral load is low, the detection rate is also low. This consequently leads to the occasional occurrence of false results. Similarly, with the use of this method, the severity and progression of the virus cannot be known. Despite these disadvantages, the rRT-PCR method of diagnosis has been performing well since the outbreak of the coronavirus. However, the number of people tested is not yet satisfactory. This can be attributed to the fact that this method of diagnosis is relatively costly.

The authors in Lieberman et al. (2020), Nalla et al. (2020) stated that, in ideal settings, NAATs have the analytic sensitivity. This implies NAATs can accurately detect the low levels of viral RNA in test samples that are known to contain viral RNA. However, the authors reported that there has not been a systematic evaluation of the accuracy and predictive values of SARS-CoV-2 NAATs. A report from the United States (US) Food and Drug Administration (FDA) stated that approximately 3% of results with BD SARS-CoV-2 Reagents for the BD Max System test, were false-positive results (FDA, 2020). Hence clinical laboratory staff and health care personnel in the US were cautioned due to the increased risk of false-positive results with the test. Therefore, the FDA recommended that clinical laboratory staff and the health care personnel should consider carrying out an alternate authorized test to confirm any result presumed to be positive from tests.

It was reported that false-negative rates ranged from 5% to 40% (Arevalo-Rodriguez et al., 2020; Long et al., 2020; Weissleder et al., 2020). Fang et al. (2020) reported cases in China where fifty one patients with fever or acute respiratory symptoms, were ultimately tested positive using the SARS-CoV-2 RT-PCR test, but in the initial test carried out, 15 patients (29%) had negative results. In a similar study (Lee et al., 2020) in Singapore, where 70 patients were tested positive, the initial nasopharyngeal testing was negative in eight patients (11%). These studies established that some patients were repeatedly negative in the initial testing but they later tested positive after rounds of four or more tests. This implies that there are occurrences of false-negative results and therefore, some rounds of testing are recommended, in order to confirm the accuracy of the results.

In Alpdagtas et al. (2020), various clinical diagnostic methods for COVID-19 were evaluated with emphasis on their pros and cons, vis-à-vis their performances. Immunological and RT-PCR testing methods were

identified as the best diagnostic methods for COVID-19. However, the knowledge of these diagnostic methods lies only with professionally trained physicians. Non-professional personnel cannot apply it on their own. Neither can a patient. Thus, the authors recommended the production of point-of-care (POC) diagnostic devices that can diagnose with little or no support from physicians. In addition, accuracy is not always guaranteed using the diagnostic method, hence there is a need for the development of better methods with a higher level of practicality, accuracy and precision. Similarly, in Uygun-Can and Acar-Bolat (2020), RT-PCR and CT testing methods were used to detect COVID-19 in pregnant women and it was established by the authors that the combination of the two testing tools gave an accurate and safe diagnosis. This implies that a combination of two or more clinical methods for COVID-19 diagnosis guarantees better accuracy and precision.

Other examples of clinical diagnostic methods have been used to diagnose COVID-19 and are reported in literature: Nucleic Acid Test, CT, immunological examinations, lung ultrasound, F-FDG PET/CT (Ardakani et al., 2020; Mertens et al., 2020; Wan et al., 2020; Xie et al., 2020); RT-PCR, POC, Immunoassays for antibody to virus (Giri et al., 2020; He et al., 2020; Wu et al., 2020); POC, multiplex assays, CT imaging, genome sequencing, Electron Microscopy, and PCR (Luo et al., 2020; Udugama et al., 2020); oligonucleotide-based molecular detection, POC immuno-diagnostics, radiographical analysis/sensing system, biosensing prototypes, and RT-PCR (Mahapatra and Chandra, 2020); clinical computer-aided diagnosis (CAD) using machine learning algorithms (Ardakani et al., 2021); artificial intelligence (AI) enabled medical imaging (Yuan et al., 2020); Molecular-based assay, POC, rRT-PCR (Yang et al., 2020).

Our deductions are as follows:

- Most of the studies focused on measuring the accuracy of the clinical methods for COVID-19 diagnosis.
- The studies provided information that helps to guide health professionals to conduct error-free COVID-19 diagnostic tests. Similarly, the information guides the researchers to identify limitations with each clinical method and hence develop better clinical methods for detecting COVID-19 cases.
- The works affirmed that the use of a single clinical method to detect COVID-19 does not guarantee accurate results as expected. However better performance is always witnessed when two or more of the clinical methods are combined in the process of diagnosing COVID-19 cases. Thus, health personnel are advised to explore the combination of methods in the process of COVID-19 diagnosis.
- Clinical methods mostly used are RT-PCR, POC, Molecular-based assay and chest CT.
- Test sensitivity is likely influenced by specimen quality, illness duration and specific assay.

The limitations that are common to all the clinical methods are as follows:

- Accuracy is not always guaranteed with the use of one clinical method for diagnosis. Therefore, there is a need to carry out an alternate authorized test to confirm the sensitivity and specificity. The combination of two or more methods of testing helps to confirm the accuracy of the test results.
- They are laboratory tests that require well equipped laboratories. Hence the establishment of the test laboratories is expensive and the test is relatively expensive and it takes some time.
- The testing machines are relatively expensive (e.g., PCR machines) and few laboratories could afford them.
- Physicians/patients need to travel to a competent laboratory to access the PCR machine and this may take some hours or days depending on the location of the patients and the nearest available COVID-19 test laboratory. Hence, results are not received immediately.

- e. The methods require well trained medical personnel to run the tests in the laboratories; however, there is a dearth of qualified medical personnel for the laboratories and the few personnel available are overstretched and fatigued due to the increasing number of cases of COVID-19. Hence there are possibilities of false-negative results in some cases.
- f. Performance is not optimal with the use of the clinical diagnostic methods and hence, the need to apply artificial intelligence-based systems using computational algorithms, helps to ensure better performance in terms of balanced accuracy, precision, specificity and sensitivity, Bookmaker informedness (BM), and MCC.

2.3. Computational intelligence-based methods used for diagnosing COVID-19

In this sub-section we did a review of past works that have applied computational intelligence-based algorithms for diagnosing COVID-19 with the view to identify the patients' symptoms, performances, and the metrics used for measuring their performances and limitations.

Convolutional Neural Network (CNN) was used in [Mahmud et al. \(2020\)](#) to develop CovXNet model that was used to detect COVID-19 and pneumonia. The model had an accuracy value of 97.4%. Similarly, COVIDScreen was developed in [Singh et al. \(2021\)](#) using CNN. The model helped to carry out the differential diagnosis of COVID-19 with an accuracy of 98.67%. In the same light, SVM was applied in [Jin et al., \(2021\)](#) for examining chest X-ray radiograph with the view to carry out the differential diagnosis of COVID-19. The accuracy recorded was 98.642%. In China, a team of researchers developed LR-based model to identify the independent predictors of COVID-19 severity in suspected cases ([Xu et al., 2020](#)); a similar research was also reported in [Iwendi et al. \(2020\)](#) where Random Forest (RF) model was used for predicting the severity of COVID-19 in infected patients. In the same manner, LR was used to predict mortality risk in COVID-19 patients and the accuracy was measured at 70% ([Bhandari et al., 2020](#)). Also, RF algorithm was applied to predict the mortality of COVID-19 patients and the accuracy of 95% was obtained. [Fleitas et al. \(2020\)](#) also applied multivariate LR to identify COVID-19 symptoms and infected cases of COVID-19 were detected with the specificity of 46%. In [Silahudin and Holidin \(2020\)](#), an expert system was developed for diagnosing COVID-19 using the Naïve Bayes (NB) technique. Similarly, Naïve Bayes Decision Support System (DSS) was presented in [Awwalu et al. \(2020\)](#) for COVID-19 detection. Fuzzy Cognitive Map (FCM) was applied in [Groumpos \(2020\)](#) to examine the whole spectrum of COVID-19 by considering the causality factors. The authors could not guarantee the performance of the model because real-life data required were not available. However, the model was tested using data that were generated from the literature. The strength of FCM in COVID-19 classification based on causality factors was established and this gave the directions for the future research.

Hybrid models were also developed for COVID-19 detection. For example ([Sethy et al., 2020](#)), combined SVM and CNN were used to develop a model for detection of the COVID-19 patients among patients infected with pneumonia and healthy people. Accuracy and specificity achieved were 95.33% each. [Alakus and Turkoglu \(2020\)](#) evaluated six different clinical predictive models for detecting COVID-19 infection using 18 laboratory findings from 600 patients. The techniques considered in the models are: CNN, Recurrent Neural Networks (RNN), Artificial Neural Network (ANN), Long-Short Term Memory (LSTM), CNNRNN and CNNLSTM. The evaluation results showed 86.66% accuracy, 91.89% F1-score, 86.75% precision, 99.42% recall and 62.50% AUC. Also LR, DT (decision tree), SVM, DNN and RF (Random forest) were applied for early detection of COVID-19 and the performance results are 0.971 AUC, and 0.82 sensitivity ([Sun et al., 2020](#)). CNN and DNN were used in [Hassan-tabar et al. \(2020\)](#) to diagnose COVID-19 patients with CNN having 93.2% accuracy, and 96.1% sensitivity while DNN has 83.4% accuracy and 86% sensitivity.

Similarly CNN and LR were used to develop CovNet30 system that was used to automatically diagnose COVID-19 in [Gour and Jain \(2020\)](#).

CovNet30 operates with 92.74% classification accuracy and 93.33% sensitivity. Decision tree (DT) and CNN were also used to build a classifier for detecting COVID-19 in [Yoo et al. \(2020\)](#) and the classifier works with an accuracy of 95%. CoroNet was proposed in [Khan et al. \(2020\)](#) and [Oh et al. \(2020\)](#). CoroNet is a DCNN-based model developed to detect COVID-19 infection using chest X-ray images. CoroNet operates at 89.6% accuracy, 93% precision and 98.2% recall rate. Classification algorithms adopted were deep CNN and DNN. A similar experiment was carried out in [Mukherjee et al. \(2020\)](#) using the DNN approach and the classification accuracy was 96.28%. Fuzzy logic and DNN were used in [Shaban et al. \(2021\)](#) with the performance results of 97.658% accuracy, 96.756% precision, 96.55% recall, and 96.615% F-measure.

MH-COVIDNet was proposed in [Canayaz \(2021\)](#) for diagnosing COVID-19. DNN and meta-heuristic-based feature selection techniques were adopted to develop MH-COVIDNet. X-ray images were used. The authors reported overall classification accuracy of 99.38%. In [Mansour et al. \(2021\)](#), Feature Correlated Naïve Bayes (FCNB) model was proposed and it achieved 99% detection accuracy. LR and DCNN were used to develop a classifier with an accuracy of 98.5%. In [Alqudah et al. \(2020\)](#), the classification of COVID-19 cases was done using CNN, SVM and RF algorithms with the view to compare their performances. CNN was identified with the best performance having a testing accuracy of 95.2%.

Our deduction is that the computational models focus more on the use of chest X-ray image data for diagnosing COVID-19 but not on other regular symptoms, such as fever or chills, cough, shortness of breath or difficulty breathing, fatigue, muscle or body aches, headache, loss of taste or smell, sore throat, congestion or runny nose, nausea or vomiting, and diarrhea. The models are not useful at the early stage of COVID-19 infection when the aforementioned regular symptoms are mild and it appears that one is infected with flu or malaria. At this stage, the chest X-ray images may not present the expected results because the respiratory/cardiovascular system have not been distorted as expected. As of the time of this study, the authors have not found any study that has applied any of the classifiers or combination of the classifiers using the aforementioned regular symptoms for COVID-19 diagnosis.

2.4. Quality attributes of the intelligence-based classifiers

2.4.1. Fuzzy Cognitive Map (FCM)

FCM is a knowledge representation algorithm that makes use of fuzzy graph structure to present the causal relationship between concepts and hence present the causal values between the concepts. The relation between the concepts helps to calculate the extent to which pairs of concepts impact each other. COVID-19 is associated with several symptoms and risk factors (i.e., concepts) that impact one another. The relationship and strength of pairs of symptoms/risk factors are defined based on the experiential knowledge of the medical doctors, which is fuzzy in most cases. The doctors use their discretion, based on previous experiences. FCM can be found useful to solve the fuzziness problem, associated with the classification of COVID-19 patients. The signed and weighted arcs of the FCM graph depict the causal relationship that exists among the symptoms/risk factors and hence illustrate the interconnection between the symptoms/risk factor and how the symptoms/risk factors influence one another ([Kosko, 1986](#); [Papageorgiou and Stylios, 2008](#)).

The following features of FCM as presented in [Papageorgiou and Stylios \(2008\)](#), make it fit for the classification and differential diagnosis of COVID-19:

- a. FCM is used for the acquisition and representation of causal knowledge, together with the causal knowledge reasoning process. This is needed to identify the causal strength of each of the COVID-19 symptoms relative to other symptoms.
- b. It is a neuro-fuzzy algorithm that can help to solve decision making problems such as the COVID-19 classification problem. The strength of FCM in cognitive decision making during medical diagnosis was

presented in [Chandiok and Chaturvedi \(2016\)](#). It was noted that FCM helps to represent the cognitive knowledge required in expert systems that are used for medical diagnosis. This is utilized for rational decision making and aids prediction.

- c. Similarly, FCM supports the differential diagnosis of diseases. [Lopes et al. \(2013\)](#) made use of FCM in the development of a DSS for differential diagnosis of alterations in urinary elimination.
- d. FCM's weights can be trained and updated using learning algorithms. Hence, it makes it possible to compute the weights of the relationship between all pairs of symptoms of COVID-19.

2.4.2. Support Vector Machine (SVM)

SVM is a supervised machine learning (ML) technique that is applied in the classification and regression problems. Generally, it is best applied in the classification problems ([Land and Schaffer, 2020](#); [Pisner and Schnyer, 2020](#)). SVM algorithm can process datasets with multiple continuous and categorical variables. It labels data (i.e., input and output) for classification. It is a non-probabilistic, and binary linear classifier. SVM-based models are trained, using labelled data. It is a representation of diverse classes in a hyperplane in a multidimensional space. SVM generates the hyperplane in an iterative form with the view to minimize errors. SVM focuses on dividing datasets into different classes in order to find a maximum marginal hyperplane (MMH). Thus, classification provides the basis to train the system for data processing. The support vectors are the data points, closest to the hyperplane while the hyperplane is a decision space that is divided between a set of objects having different classes. The algorithms achieve the best separation of data with the boundary around the hyperplane being maximized and even between both sides. The SVM classification algorithm is fast and dependable and it performs well with a limited amount of data to analyze.

The following are features of SVM that make it fit for classification and differential diagnosis of COVID-19:

- a. SVM is a binary linear classifier ([Noble, 2006](#); [Pisner and Schnyer, 2020](#)) and it is best applied in two-group classification problems. In this light, SVM can be used to build learning models that could accurately classify COVID-19 patients into two groups (i.e., True Positive COVID-19 and True Negative COVID-19 patients) based on the COVID-19 dataset available.
- b. SVM is relatively simple and flexible to address classification problems ([Pisner and Schnyer, 2020](#)).
- c. SVMs distinctly produce the balanced predictive performance in cases where the sample data sizes are limited ([Pisner and Schnyer, 2020](#)). This makes it suitable, even with limited COVID-19 datasets.

2.4.3. Decision Tree (DT)

DT is applied in classification and regression problems. It embraces supervised learning method. Application of decision tree for the classification of COVID-19 cases using X-ray imaging was reported in [Yoo et al. \(2020\)](#). Similarly, DT algorithm has been applied in [Atieh et al. \(2019\)](#) for predicting peri-implant disease. Also, it has been used for the diagnosis of diabetic patients, as presented in [Kamadi et al. \(2016\)](#). Advantages of the DT are as follows ([Gupta, 2017](#)): it is simple and easy to understand, interpret, and visualize; variable screening and feature selection are implicitly performed; it accommodates numerical and categorical data; it solves multi-output problems; relatively little effort is required for data preparation and the performance of the tree is not influenced by nonlinear relationships that are between parameters. However, DTs have the following shortcomings ([Gupta, 2017](#)): overfitting problem and variance; needs to be lowered using bagging and boosting methods; creation of biased trees if some classes dominate; and optimal decision tree is not guaranteed in cases of greedy algorithms.

2.4.4. Naïve Bayes (NB)

NB is an intuitive classification method that uses Bayes' theorem and

assumed independence among predictors. Even though the complete independence among predictors is impossible in real-life situations ([Dinant, 2018](#); [Ray, 2017](#)). It uses supervised learning method. NB is used with large datasets. It is simple, fast, and easy to implement and the classification accuracy is better compared to other classification algorithms, most especially when the assumption of independence predictor holds. There are Gaussian, Multinomial and Bernoulli types of NB. It takes less time for training because small training data are required for NB to estimate the test data. It linearly scales with the number of predictor features and data points. It is applied to binary and multi-class classification problems. NB model was used to diagnose COVID-19 patients in [Mansour et al. \(2021\)](#). Similarly, [Silahudin and Holidin \(2020\)](#) modeled expert systems using the NB technique to diagnose COVID-19 and [Awwalu et al. \(2020\)](#) developed a DSS for COVID-19 diagnosis using a multinomial NB algorithm.

2.4.5. Multilayer Perceptron (MLP)

MLP is a feedforward ANN that has a minimum of three layers of nodes or neurons (i.e. input layer, hidden layer and output layer). Each neuron makes use of non-linear activation function except the input neurons. MLP embraces backpropagation algorithm for training. The well-arranged network of neurons helps data modelling with the use of machine learning algorithms and hence facilitates accurate processing vis-à-vis accurate decision making. MLP is trained to carry out a given task and MLP-based models help to analyze data and hence recognize patterns within the data. The merits of using MLP are as follows: models complex and non-linear problems; performs very well with large data; it is capable of generalizing; its fault tolerance is high; good for pattern recognition. In the light of aforementioned merits, MLP has been adopted to develop models for diagnosing COVID-19 with remarkable performance. For example, MLP was applied in [Salman et al. \(2020\)](#) for X-ray images classification to detect COVID-19 in patients. Similarly COVID-19 early vision diagnosis using MLP was proposed in [Hammam et al. \(2020\)](#). Also, MLP and LR were combined to develop a hybrid model for COVID-19 diagnosis in [Mohammadi et al. \(2021\)](#). The authors established good performance for the MLP-based models in terms of accuracy, sensitivity and specificity. However, some limitations are attributed to MLP, such as computational intensiveness and time consuming, problem of scaling, and model performance dependence on quality of training. However, solution is not always guaranteed.

2.4.6. Logistic regression (LR)

LR is the class of supervised learning techniques that is applied in classification problems. It is used for predicting the probability of a binary-based dependent variable. Thus, the dependent variable has data coded as either 0 (negative/no) or 1 (positive/yes). An example of logistic regression equation is presented in Equation (1) ([Brownlee, 2016](#)):

$$y = e^{(b_0 + b_1 * x)} / (1 + e^{(b_0 + b_1 * x)}) \quad (1)$$

where y : predicted output; b_0 : bias or intercept term; b_1 : the coefficient for the single input value (x). Each column in the input data has an associated b coefficient (a constant real value) that must be learned from the training data.

LR is a simple machine learning algorithms and it is well applied in medical diagnostic problems for the detection of diseases, making it a good algorithm for classification of the COVID-19 patients. For example, LR was applied in several studies ([Roland et al., 2020](#); [Shang et al., 2020](#); [Song et al., 2020](#)) to predict the severity of COVID-19 in infected patients. Also LR-based system was proposed in [Fink et al., \(2020\)](#) for the validation of the results of COVID-19 diagnostic prediction at the time of admission in the hospital.

2.4.7. Other deep learning classifiers

Deep learning classifiers, such as Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Radial Basis Function

Networks (RBFNs), Self Organizing Maps (SOMs), Deep Belief Networks (DBNs), Restricted Boltzmann Machines (RBMs) and Autoencoders are other algorithms that could be applied for disease diagnosis but we did not consider them in this study because they do not fit for our dataset. Rather they are most commonly applied to analyze visual imagery, time series data, natural-language processing, and machine translation (Biswal, 2021).

3. Material and methods

3.1. Data collection and data pre-processing

The data are obtained from <https://github.com/burakalakus/COVID-19-Clinical> and contain 600 entries of patient records.

3.2. Data pre-processing and modeling

In order to overcome overfitting and outliers, there is need for data pre-processing. Data pre-processing were performed using WEKA and Python library Scikit-learn (sklearn). In this study, we experimented with LR, SVM, NB, DT, MLP, FCM and DNN algorithms by calibrating their parameters. The algorithms are applied to the resampled data to eliminate class imbalance (520 negative cases and 80 positive cases of COVID-19) using random undersampling and oversampling approach. The COVID-19 clinical dataset was divided into a training dataset (80%) and a testing dataset (20%). This study uses the training dataset to train the COVID-19 classification model and uses the testing dataset to measure model performance and to ensure that the results of the classification model are robust. According to Elujide et al. (2021), classification problems can be modeled using single-label and multi-label approach. This study employed a single-label approach with binary classification problem. For the deep neural network model, a two-layer neural network was implemented with the two COVID-19 indicators to classify the clinical COVID dataset.

3.3. Measure of performance

The performance of the classification algorithms is measured based on the following performance metrics: accuracy, precision, recall, MCC, balanced accuracy and Bookmaker informedness (BM).

4. Results and discussion

We did a quantitative analysis of the classifiers. The clinical dataset on COVID-19 contains 600 entries of patient records comprising of an ID, set of symptoms and status (label) features. This section answers: **RQ-1:** What are the classifiers appropriate for differential diagnosis of COVID-19? **RQ-2:** What is the performance of each of the classifiers in terms of accuracy, precision, recall, F-measure, MCC, balanced accuracy, and BM?

We empirically tested and verified the efficacy of the following classification algorithms: LR, SVM, NB, DT, MLP, FCM and DNN. The algorithms were subjected to random undersampling and oversampling. The classification algorithms were subject to random undersampling in order to convert class imbalance to balanced class on the target variable (520 negative cases and 80 positive cases of COVID-19). We evaluated the performances of the classification algorithms using the following metrics: accuracy, precision, recall, F-measure, and MCC while balanced accuracy, BM, MCC, accuracy, precision, recall, F-measure are considered for FCM based on percentage split (80% for training and 20% for testing). The COVID-19 dataset experiments were performed using python and R.

According to the Chicco and Jurman (2020), most data scientists and machine learning experts use confusion matrix to evaluate binary classification. Few studies recently reported that it is not adequate to base the performance evaluation results on class imbalance dataset on accuracy and F1 score, as well as on MCC result because it puts the ratio between

the positive and negative into consideration. The closer MCC is to +1, the better the binary classification; the closer MCC is to -1, the worse the binary classification. Chicco et al. (2021) claimed that MCC is a more reliable performance metric to put into consideration over balanced accuracy, BM and markedness (MK) in evaluating binary classification.

We compared the results on the use of random undersampling, integrated with the classification algorithms based on the use of percentage split. As shown in Table 1, with class imbalance, MLP outperforms LR, NB, DT and SVM in accuracy, precision, recall, F-measure and MCC. Similarly, DNN has the best performance in accuracy, recall and F-measure. As shown in Table 2, without class imbalance, MLP outperforms LR, NB, DT and SVM in accuracy, precision, recall, F-measure and MCC, while DNN performs best with the use of oversampling.

Furthermore, we compared the results on the dataset with a class imbalance on percentage split of 80% for training and 20% for testing with dataset without class imbalance (use of random undersampling and oversampling is integrated on the classification algorithms to eliminate the class imbalance on the percentage split of 80% for training and 20% for testing) in python and DNN with the following parameters: epoch of 150, batch_size of 10, loss = binary_crossentropy, and adam optimizer. Two-layer was added to a sequential model from Keras, with ReLu and Sigmoid activation functions.

Comparing Tables 1 and 2, it was discovered that the classification algorithms in Table 1 perform better with the traditional performance metrics for evaluation (i.e., accuracy, precision, recall, and F-measure) but it was poor in performance with the MCC performance metric. The performance in Table 1 is due to overfitting. While in Table 2, their performances dropped in terms of accuracy, precision, recall and F-measure. Therefore, our findings show that without class imbalance, the rate of improvement of performance with MCC as a performance metric is very high for all the classifiers while there is a drop in performances for other metrics. This aligns with the claims of Chicco and Jurman (2020) that MCC is the best performance metric to determine the best classifier, without class imbalance. We noticed that in Table 1, all the performance metrics for machine learning algorithms were higher than 80% in the MLP and DNN and this makes them better classifier over others but the MCC is very far from 100%; while in Table 2, DNN is the best classifier even though the MCC value is close to 100%.

In addition, this report also summarizes the development of a FCM model that analyses COVID-19 symptoms and determines status as either positive or negative. The FCM model was developed with the twenty (20) concepts of the COVID-19 dataset. Weights for each relationship between concepts were extracted from a weight matrix which was in term extracted and trained from the dataset, using a simplified version of the Hebbian Learning algorithm given by Equation (2).

$$w_{ij}(k+1) = w_{ij}(k) + \alpha(y_i(k) * x_j(k)) \quad (2)$$

The weight matrix and imported data frame of the data were then pre-processed by scaling column values in the [0, 1] as per the requirement of the parameters of the inference function of the FCM model. The dataset was split into 80% training set and 20% testing set, i.e., 480 records were used in developing and training the weight matrix and 120 were used to test the dataset with class imbalance, while another experiment was also carried out on the dataset without class imbalance after applying the random undersampling to it. The inference results from running the *fcn.infer* function in twenty-five (25) iterations were stored in an array.

Table 1
COVID-19 clinical dataset with class imbalance on percentage split (80-20).

Performance metrics	LR	SVM	NB	DT	MLP	DNN
Accuracy	86.7	87.5	84.2	82.5	88.3	88.3
Precision	86.7	87.5	84.2	82.5	88.3	86.0
Recall	85.8	77.9	85.6	83.0	86.3	88.0
F-measure	86.2	82.4	84.8	82.8	86.9	87.0
MCC	31.2	-3.3	29.9	17.7	31.9	25.6

Table 2
COVID-19 clinical dataset without class imbalance on percentage split (80-20).

Performance metrics	LR (US)	SVM (US)	NB (US)	DT (US)	MLP (US)	DNN (US)	DNN (OS)	LR (OS)	SVM (OS)	NB (OS)	DT (OS)	MLP (OS)
Accuracy	78.1	78.1	81.3	65.6	81.3	84.4	93.8	80.2	79.3	82.45	66.8	<u>81.8</u>
Precision	78.1	78.1	81.3	65.6	81.3	85.0	94.0	80.2	78.8	83.1	66.7	<u>81.6</u>
Recall	82.6	82.6	81.1	72.6	84.4	84.0	94.0	83.1	82.9	82.4	73.1	<u>85.2</u>
F-measure	78.4	78.4	80.8	65.9	81.5	84.0	94.0	79.2	79.8	81.4	66.3	<u>82.2</u>
MCC	59.8	59.8	59.2	37.8	64.5	69.0	88.0	60.3	61.3	60.1	38.2	<u>65.2</u>

Note: undersampling (US); oversampling (OS).

These results were compared with the actual labels of the test data. Sigmoid function was used in this study. Table 3 shows the comparative summary of the results.

We compared the results on the Fuzzy Cognitive Map for the dataset with class imbalance on percentage split of 80% for training and 20% for testing with dataset without class imbalance (use of random undersampling integrated on the classification algorithms to eliminate the class imbalance on the percentage split of 80% for training and 20% for testing). It was discovered that the FCM without class imbalance outperforms the FCM with the class imbalance in all the performance evaluation metrics, except in MCC. Our findings, as presented in Table 3, do not support the claims of Chicco et al. (2021) which state that MCC performs better than balanced accuracy and BM. Our results in Table 3 reveal that balanced accuracy outperforms BM and MCC.

5. Conclusion and managerial implication

5.1. Conclusion

The increasing number of global cases of COVID-19 infection is alarming and the large number of infected people that flood the hospitals on daily basis has caused an overstretching of the available medical facilities as well as the healthcare workers. The patients require reliable and accurate diagnosis and treatments. There are reports that with the use of the clinical methods for COVID-19 diagnosis, some people who were initially tested positive for COVID-19 and who were having some underlying diseases, turned out having negative results after series of further tests. This implies that true positive and true negative results are not always guaranteed.

In this study, having analyzed the quality attributes of the clinical methods for diagnosing COVID-19, we further employed some classifiers which constitute intelligence-based methods, which could be applied to the early diagnosis of COVID-19. The classifiers are considered to complement the clinical diagnosis methods. The classifiers employed for the experiment are LR, SVM, NB, DT, MP, FCM and DNN. We did experiments with our data to determine the best classification technique in terms of accuracy, precision, recall, F-measure, MCC, balanced accuracy, and BM, based on percentage split (80% for training and 20% for testing). Our results showed that with class imbalance, MLP and DNN outperform LR, NB, DT, SVM and FCM in accuracy, precision, recall, F-measure and MCC (See Table 1), but without class imbalance, MLP, FCM and DNN outperform LR, NB, DT and SVM in accuracy, precision, recall, F-measure, MCC, BM, and balanced accuracy (See Tables 2 and 3).

Table 3
Performance evaluation metrics on FCM.

Performance metrics	FCM with class imbalance	FCM without class imbalance
Accuracy	79.2	87.5
Precision (PPV)	85.3	87.1
Recall (TPR)	79.5	100.0
F-measure	82.3	93.1
MCC	49.0	42.0
BM	58.2	87.1
Balanced accuracy	79.1	93.5

It is worth noting that with class imbalance, their performances are poor using the MCC performance metric, but without class imbalance, MCC values increase for all the classifiers while there is a drop in performances for other metrics. This agrees with the claims of Chicco and Jurman (2020) that MCC is a good performance metric to determine the best classifier without class imbalance. We also discovered that without class imbalance, FCM performs better for all the performance metrics, compared to the performance with class imbalance. The only exception is with MCC, whose value dropped without class imbalance (See Table 3). Thus, MCC performs better than balanced accuracy and BM.

Considering the relatively good performance values of the tested classification algorithms (i.e., MLP, LR, NB, DT, SVM, FCM and DNN), intelligence-based systems can be developed for COVID-19 diagnosis using these algorithms, but our results present MLP, FCM and DNN as better algorithms that healthcare system developers should adopt for early differential diagnosis of COVID-19. Moreover, the test of performance must not be limited to the classic performance metrics for evaluation (i.e., accuracy, precision, recall, and F-measure), other performance metrics, such as MCC, balanced accuracy and bookmaker informedness must also be considered. In the light of this, our future works will be considering the development and implementation of a COVID-19 smart medical diagnostic system (i.e., C-19-SmartMed) that will be able to differentially diagnose patients for COVID-19 based on the common symptom (i.e., fever or chills, cough, shortness of breath or difficulty breathing, fatigue, muscle or body aches, headache, loss of taste or smell, sore throat, congestion or runny nose, nausea or vomiting, and diarrhea) and using classifiers such as MLP, FCM and DNN. The system is envisaged to complement the effort of the physician.

5.2. Managerial implication

Automated healthcare systems are required to complement the services of the medical personnel in the present circumstances of COVID-19 pandemic with rising cases of new variants and infection. This study has identified MLP, FCM and DNN as better classifiers over LR, NB, DT and SVM, that healthcare software system developers can adopt to develop intelligence-based decision support systems and expert systems which both medical personnel and patients can use for quick differential diagnosis when the following common symptoms are presented: fever or chills, cough, shortness of breath or difficulty breathing, fatigue, muscle or body aches, headache, loss of taste or smell, sore throat, congestion or runny nose, nausea or vomiting, and diarrhea.

This study suggests a paradigm shift from the use of chest X-ray image data on computational systems that are currently used to diagnose COVID-19. Therefore, the management board in the health sector should provide supports for the development of the new application software that could easily diagnose patients based on the common symptoms stated above. This is better than exposing the patients to consistent chest X-ray which is not easily accessible, and not economical for the patients, and which has side effect in the long run. By doing so, there will be increasing access to quick and economical healthcare services when one is having a feeling of COVID-19 infection particularly in low-income countries of Africa where there is a dearth of medical personnel and poor medical facilities.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Acknowledgment

We acknowledge the contributions of all the medical practitioners that supported us in the course of this research. We express our gratitude to them.

References

- Alakus, T.B., Turkoglu, I., 2020. Comparison of deep learning approaches to predict COVID-19 infection. *Chaos, Solit. Fractals* 140 (Nov.), 1–7.
- Alpdagtas, S., Ilhan, E., Uysal, E., Sengor, M., Ustundag, C.B., Gunduz, O., 2020. Evaluation of current diagnostic methods for COVID-19. *APL Bioeng.* 4 (4), 041506.
- Alqudah, A.M., Qazan, S., Alquran, H., Qasmieh, I.A., Alqudah, A., 2020. COVID-19 detection from x-ray images using different artificial intelligence hybrid models. *Jordan J. Elect. Eng.* 6 (6), 168–178.
- Anne, H., 2020. The 12 deadliest viruses on Earth. <https://www.livescience.com/56598-deadliest-viruses-on-earth.html> (Accessed 15 Jan 2021).
- Ardakani, A.A., Acharya, U.R., Habibollahi, S., Mohammadi, A., 2021. COVIDiag: a clinical CAD system to diagnose COVID-19 pneumonia based on CT findings. *Eur. Radiol.* 31 (1), 121–130.
- Ardakani, A.A., Kanafi, A.R., Acharya, U.R., Khadem, N., Mohammadi, A., 2020. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. *Comput. Biol. Med.* 121 (Jun.), 1–10.
- Arevalo-Rodriguez, I., Buitrago-Garcia, D., Simancas-Racines, D., Zambrano-Achig, P., Del Campo, R., Ciapponi, A., et al., 2020. False-negative results of initial RT-PCR assays for COVID-19: a systematic review. *PLoS One.* 15 (12), e0242958.
- Atieh, M.A., Pang, J.K., Lian, K., Wong, S., Tawse-Smith, A., Ma, S., Duncan, W.J., 2019. Predicting peri-implant disease: Chi-square Automatic Interaction Detection (CHAID) decision tree analysis of risk indicators. *J. Periodontol.* 90 (8), 834–846.
- Awwalu, J., Umar, N.A., Ibrahim, M.S., Nonyelum, O.F., 2020. A multinomial naïve Bayes decision support system for covid-19 detection. *Fudma J. Sci.* 4 (2), 704–711.
- Bhandari, S., Shaktawat, A.S., Tak, A., Patel, B., Shukla, J., Singhal, S., et al., 2020. Logistic regression analysis to predict mortality risk in COVID-19 patients from routine hematologic parameters. *Ibnosina J. Med. Biomed. Sci.* 12 (2), 123–129.
- Biswal, A., 2021. Top 10 deep learning algorithms You should know in 2021. *Simplilearn*. <https://www.simplilearn.com/tutorials/deep-learning-tutorial/deep-learning-algorithms>. (Accessed 27 October 2021).
- Brownlee, J., 2016. Logistic regression for machine learning. *Mach. Learn. Alg.* <https://machinelearningmastery.com/logistic-regression-for-machine-learning/>. (Accessed 27 October 2021).
- Caliendo, A.M., Hanson, K.E., 2021. Coronavirus disease 2019 (COVID-19): diagnosis. <https://www.uptodate.com/contents/coronavirus-disease-2019-covid-19-diagnosis> (Accessed 15 February 2021).
- Canayaz, M., 2021. MH-COVIDNet: diagnosis of COVID-19 using deep neural networks and meta-heuristic-based feature selection on X-ray images. *Biomed. Signal Process. Control.* <https://doi.org/10.1016/j.bspc.2020.102257>.
- Chandiok, A., Chaturvedi, D., 2016. Cognitive decision support system for medical diagnosis. In: Paper presented at the 2016 International Conference on Computational Techniques in Information and Communication Technologies (ICCTICT).
- Chicco, D., Jurman, G., 2020. The advantages of the Matthews Correlation Coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genom.* 21 (1), 1–13.
- Chicco, D., Tötsch, N., Jurman, G., 2021. The Matthews Correlation Coefficient (MCC) is more reliable than balanced accuracy, bookmaker informedness, and markedness in two-class confusion matrix evaluation. *BioData Min.* 14 (1), 1–22.
- Dai, W., Zhang, H., Yu, J., Xu, H., Chen, H., Luo, S., Lei, Y., 2020. CT imaging and differential diagnosis of COVID-19. *Can. Assoc. Radiol. J.* 71 (2), 195–200.
- de Moraes Lopes, M.H.B., Ortega, N.R.S., Silveira, P.S.P., Massad, E., Higa, R., de Fátima Marin, H., 2013. Fuzzy cognitive map in differential diagnosis of alterations in urinary elimination: a nursing approach. *Int. J. Med. Inf.* 82 (3), 201–208.
- Dinant, C., 2018. What's so naïve about naïve Bayes? <https://towardsdatascience.com/whats-so-naive-about-naive-bayes-58166a6a9eba> (Accessed 22 February 2021).
- Elujide, I., Fashoto, S.G., Fashoto, B., Mbunge, E., Folurunso, S.O., Olamijuwon, J.O., 2021. Application of deep and machine learning techniques for multi-label classification performance on psychotic disorder diseases. *Inf. Med. Unlocked* 23 (2), 100545.
- Fang, Y., Zhang, H., Xie, J., Lin, M., Ying, L., Pang, P., Ji, W., 2020. Sensitivity of chest CT for COVID-19: comparison to RT-PCR. *Radiology.* 296 (2), E115–E117.
- FDA, 2020. False positive results with BD SARS-CoV-2 Reagents for the BD Max system - letter to clinical laboratory staff and health care providers. <https://www.fda.gov/medical-devices/letters-health-care-providers/false-positive-results-bd-sars-cov-2-reagents-bd-max-system-letter-clinical-laboratory-staff-and> (Accessed 14 February 2020).
- Fink, D., Khan, P., Goldman, N., Cai, J., Hone, L., Mooney, C., et al., 2020. Development and internal validation of a diagnostic prediction model for COVID-19 at time of admission to hospital. *QJM: Monthly J. Assoc. Phys.* 114 (10), 699–705.
- Fleitas, P.E., Paz, J.A., Simoy, M.I., Vargas, C., Cimino, R.O., Krolewiecki, A.J., Aparicio, J.P., 2020. Understanding the value of clinical symptoms of COVID-19. A logistic regression model. <https://www.medrxiv.org/content/medrxiv/early/2020/10/16/2020.10.07.2020719.full.pdf>. (Accessed 24 February 2021).
- Giri, B., Pandey, S., Shrestha, R., Pokharel, K., Ligler, F.S., Neupane, B.B., 2020. Review of analytical performance of COVID-19 detection methods. *Anal. Bioanal. Chem.* 413 (5), 35–48.
- Gour, M., Jain, S., 2020. Stacked convolutional neural network for diagnosis of covid-19 disease from x-ray images. Preprints. <https://arxiv.org/pdf/2006.13817.pdf>. (Accessed 25 February 2021).
- Groumpos, P.P., 2020. A new mathematical model for COVID-19: a fuzzy cognitive map approach for coronavirus diseases. In: Paper presented at the 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA).
- Gupta, P., 2021. Decision trees in machine learning. <https://towardsdatascience.com/decision-trees-in-machine-learning-641b9c4e8052> (Accessed 21 Feb 2021).
- Hammam, A.A., Elmousalami, H.H., Hassanien, A.E., 2020. Stacking deep learning for early COVID-19 vision diagnosis. In: *Big Data Analytics and Artificial Intelligence against COVID-19: Innovation Vision and Approach*. Springer, pp. 297–307.
- Hassantabar, S., Ahmadi, M., Sharifi, A., 2020. Diagnosis and detection of infected tissue of COVID-19 patients based on lung X-ray image using convolutional neural network approaches. *Chaos, Solit. Fractals* 140 (C), 1–12.
- He, J.-L., Luo, L., Luo, Z.-D., Lyu, J.-X., Ng, M.-Y., Shen, X.-P., Wen, Z., 2020. Diagnostic performance between CT and initial real-time RT-PCR for clinically suspected 2019 coronavirus disease (COVID-19) patients outside Wuhan, China. *Respir. Med.* 168 (Jul.), 105980.
- Iwendi, C., Bashir, A.K., Peshkar, A., Sujatha, R., Chatterjee, J.M., Pasupuleti, S., et al., 2020. COVID-19 patient health prediction using boosted random forest algorithm. *Frontiers in public health* 8 (Jul.), 1–9.
- Jain, B., 2017. The key role of differential diagnosis in diagnosis. *Diagnosis* 4 (4), 239–240.
- Jin, W., Dong, S., Dong, C., Ye, X., 2021. Hybrid ensemble model for differential diagnosis between COVID-19 and common viral pneumonia by chest X-ray radiograph. *Comput. Biol. Med.* 131 (Apr.), 1–12.
- Kamadi, V.V., Allam, A.R., Thummala, S.M., 2016. A computational intelligence technique for the effective diagnosis of diabetic patients using principal component analysis (PCA) and modified fuzzy SLIQ decision tree approach. *Appl. Soft Comput.* 49 (C), 137–145.
- Khan, A.I., Shah, J.L., Bhat, M.M., 2020. CoroNet: a deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Comput. Methods Progr. Biomed.* 196 (Nov.), 1–10.
- Kosko, B., 1986. Fuzzy cognitive maps. *Int. J. Man Mach. Stud.* 24 (1), 65–75.
- Land, W.H., Schaffer, J.D., 2020. The support vector machine. In: *The Art and Science of Machine Intelligence*. Springer, Berlin, pp. 45–76.
- Lee, T.H., Junhao Lin, R., Lin, R.T., Barkham, T., Rao, P., Leo, Y.-S., et al., 2020. Testing for SARS-CoV-2: can we stop at 2? *Clin. Infect. Dis.* 71 (16), 2246–2248.
- Lieberman, J.A., Pepper, G., Naccache, S.N., Huang, M.-L., Jerome, K.R., Greninger, A.L., 2020. Comparison of commercially available and laboratory-developed assays for in vitro detection of SARS-CoV-2 in clinical laboratories. *J. Clin. Microbiol.* 58 (8), 1–6.
- Long, C., Xu, H., Shen, Q., Zhang, X., Fan, B., Wang, C., et al., 2020. Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT? *Eur. J. Radiol.* 126 (1), 1–21.
- Long, D.R., Gombor, S., Hogan, C.A., Greninger, A.L., Shah, V.O.R., Bryson-Cahn, C., et al., 2020. Occurrence and timing of subsequent SARS-CoV-2 RT-PCR positivity among initially negative patients. *Clin. Infect. Dis.* 72 (1), 323–326.
- Luo, N., Zhang, H., Zhou, Y., Kong, Z., Sun, W., Huang, N., Zhang, A., 2020. Utility of chest CT in diagnosis of COVID-19 pneumonia. *Diagn. Interventional Radiol.* 26 (5), 437–442.
- Mahapatra, S., Chandra, P., 2020. Clinically practiced and commercially viable nanobio engineered analytical methods for COVID-19 diagnosis. *Biosens. Bioelectron.* 165, 112361.
- Mahmud, T., Rahman, M.A., Fattah, S.A., 2020. CovXNet: a multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. *Comput. Biol. Med.* 122 (Jul.), 1–11.
- Mann, R.S., 1990. Differential diagnosis and classification of apathy. *Am. J. Psychiatr.* 147 (1), 22–30.
- Mansour, N.A., Saleh, A.I., Badawy, M., Ali, H.A., 2022. Accurate detection of covid-19 patients based on Feature Correlated Naïve Bayes (FCNB) classification strategy. *J. Amb. Intell. Humanized Comput.* 13 (Jan.), 41–73.
- Mbunge, E., Fashoto, S.G., Akinnuwesi, B., Metfula, A., Simelane, S., Ndimiso, N., 2021. Ethics for integrating emerging technologies to contain COVID-19 in Zimbabwe. *Human Behav. Emerg. Technol.* <https://doi.org/10.1002/hbe2.277>. (Accessed 8 February 2021).
- McIntosh, K., 2020. Coronavirus disease 2019 (COVID-19): clinical features. https://www.uptodate.com/contents/coronavirus-disease-2019-covid-19-clinical-features?topicRef=128404&source=related_link (Accessed 8 Feb 2021).
- Mertens, P., De Vos, N., Martiny, D., Jassoy, C., Mirazimi, A., Cuypers, L., Vanderlinden, J., 2020. Development and potential usefulness of the COVID-19 Ag respi-strip diagnostic assay in a pandemic context. *Front. Med.* 7 (225), 1–11.
- Mohammadi, F., Pourzamani, H., Karimi, H., Mohammadi, M., Mohammadi, M., Ardalan, N., et al., 2021. Artificial neural network and logistic regression modelling to characterize COVID-19 infected patients in local areas of Iran. *Biomed. J.* 44 (3), 304–316.
- Mukherjee, H., Ghosh, S., Dhar, A., Obaidullah, S.M., Santosh, K., Roy, K., 2020. Deep neural network to detect COVID-19: one architecture for both CT Scans and Chest X-rays. *Appl. Intell.* Available at: <https://doi.org/10.1007/s10489-020-01943-6>, 1–13.

- Murthy, S.I., Das, S., Deshpande, P., Kaushik, S., Dave, T.V., Agashe, P., et al., 2020. Differential diagnosis of acute ocular pain: teleophthalmology during COVID-19 pandemic—a perspective. *Indian J. Ophthalmol.* 68 (7), 1371.
- Nalla, A.K., Casto, A.M., Huang, M.-L.W., Perchetti, G.A., Sampoleo, R., Shrestha, L., et al., 2020. Comparative performance of SARS-CoV-2 detection assays using seven different primer-probe sets and one assay kit. *J. Clin. Microbiol.* 58 (6), 1–6.
- Noble, W.S., 2006. What is a support vector machine? *Nat. Biotechnol.* 24 (12), 1565–1567.
- Oh, Y., Park, S., Ye, J.C., 2020. Deep learning covid-19 features on cxr using limited training data sets. *IEEE Trans. Med. Imag.* 39 (8), 2688–2700.
- Papageorgiou, E., Stylios, C., 2008. Fuzzy cognitive maps. *Handbook Granular Comput.* 123, 755–775.
- Pisner, D.A., Schnyer, D.M., 2020. Support vector machine. In: *Machine Learning*. Elsevier, pp. 101–121.
- Ray, S., 2017. 6 easy steps to learn naive Bayes algorithm with codes in Python and R. <https://www.analyticsvidhya.com/blog/2017/09/naive-bayes-explained/> (Accessed 22 February 2021).
- Roland, L.T., Gurrola, J.G., Loftus, P.A., Cheung, S.W., Chang, J.L., 2020. Smell and taste symptom-based predictive model for COVID-19 diagnosis. In: Paper presented at the International Forum of Allergy & Rhinology.
- Rutledge, H., 2017. A review on Isabel pro. <http://dcdm.doody.com/2017/11/a-review-of-isabel-pro/> (Accessed 11 Nov 2017).
- Salman, F.M., Abu-Naser, S.S., Alajrami, E., Abu-Nasser, B.S., Alashqar, B.A., 2020. Covid-19 detection using artificial intelligence. *Int. J. Appl. Eng. Res.* 4 (3), 18–25.
- Sand, I.K., 2015. Classification, diagnosis, and differential diagnosis of multiple sclerosis. *Curr. Opin. Neurol.* 28 (3), 193–205.
- Sethy, P.K., Behera, S.K., Ratha, P.K., Biswas, P., 2020. Detection of coronavirus disease (COVID-19) based on deep features and support vector machine. Preprints. https://www.preprints.org/manuscript/202003.0300/download/final_file. (Accessed 16 February 2020).
- Shaban, W.M., Rabie, A.H., Saleh, A.I., Abo-Elsoud, M., 2021. Detecting COVID-19 patients based on fuzzy inference engine and Deep Neural Network. *Appl. Soft Comput.* 99, 106906.
- Shang, W., Dong, J., Ren, Y., Tian, M., Li, W., Hu, J., Li, Y., 2020. The value of clinical parameters in predicting the severity of COVID-19. *J. Med. Virol.* 92 (10), 2188–2192.
- Silahudin, D., Holidin, A., 2020. Model expert system for diagnosis of covid-19 using naïve Bayes classifier. In: Paper presented at the IOP conference series: Materials Science and Engineering.
- Singh, R.K., Pandey, R., Babu, R.N., 2021. COVIDScreen: explainable deep learning framework for differential diagnosis of COVID-19 using chest X-Rays. *Neural Comput. Appl.* 10 (4), 1–22.
- Song, L., Dong, Y., Xu, M., Shi, D., Guo, W., Li, Y., et al., 2020. Analysis of prediction and early warning indexes of patients with COVID-19. *Expet Rev. Respir. Med.* 14 (12), 1257–1260.
- Sun, N.-N., Yang, Y., Tang, L.-L., Dai, Y.-N., Gao, H.-N., Pan, H.-Y., Ju, B., 2020. A prediction model based on machine learning for diagnosing the early COVID-19 patients. *medRxiv*. <https://doi.org/10.1101/2020.06.03.20120881>.
- Udugama, B., Kadhiresan, P., Kozłowski, H.N., Malekjahani, A., Osborne, M., Li, V.Y., et al., 2020. Diagnosing COVID-19: the disease and tools for detection. *ACS Nano* 14 (4), 3822–3835.
- Uygun-Can, B., Acar-Bolat, B., 2020. Clinical properties and diagnostic methods of COVID-19 infection in pregnancies: meta-analysis. *BioMed Res. Int.* <http://doi.org/10.1155/2020/1708267>.
- Uzoka, F.-M.E., Akinnuwesi, B.A., Amoo, T., Aladi, F., Fashoto, S., Olaniyan, M., Osuji, J., 2016. A framework for early differential diagnosis of tropical confusable diseases using the fuzzy cognitive map engine. *World Acad. Sci. Eng. Technol. Int. J. Comput. Elect. Automat. Control Inf. Eng.* 10 (2), 346–353.
- Wan, D., Luo, X., Dong, W., Zhang, Z., 2020. Current practice and potential strategy in diagnosing COVID-19. *Eur. Rev. Med. Pharmacol. Sci.* 24 (8), 4548–4553.
- Weissleder, R., Lee, H., Ko, J., Pittet, M.J., 2020. COVID-19 diagnostics in context. *Sci. Transl. Med.* 12 (546), 1–5.
- World Health Organization, 2020. COVID-19 weekly epidemiological update. <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-report/s/> (Accessed 31 January 2021).
- World Health Organization, 2020. Emergencies preparedness, response: SARS-CoV-2 Variants. <https://www.who.int/csr/don/31-december-2020-sars-cov2-variants/en/> (Accessed 31 January 2021).
- Wu, S.Y., Yau, H.S., Yu, M.Y., Tsang, H.F., Chan, L.W.C., Cho, W.C.S., et al., 2020. The diagnostic methods in the COVID-19 pandemic, today and in the future. *Expert Rev. Mol. Diagn.* 20 (9), 985–993.
- Xie, J., Ding, C., Li, J., Wang, Y., Guo, H., Lu, Z., et al., 2020. Characteristics of patients with coronavirus disease (COVID-19) confirmed using an IgM-IgG antibody test. *J. Med. Virol.* 92 (10), 2004–2010.
- Xu, K., Zhou, M., Yang, D., Ling, Y., Liu, K., Bai, T., et al., 2020. Application of ordinal logistic regression analysis to identify the determinants of illness severity of COVID-19 in China. *Epidemiol. Infect.* 148 (Jul.), 1–11.
- Yang, T., Wang, Y.-C., Shen, C.-F., Cheng, C.-M., 2020. Point-of-Care RNA-based diagnostic device for COVID-19. *Diagnostics*. 10 (165), 1–3.
- Yoo, S.H., Geng, H., Chiu, T.L., Yu, S.K., Cho, D.C., Heo, J., et al., 2020. Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest X-ray imaging. *Front. Med.* 7 (Jul.), 1–8.
- Yuan, X., Yang, C., He, Q., Chen, J., Yu, D., Li, J., et al., 2020. Current and perspective diagnostic techniques for COVID-19. *ACS Infect. Dis.* 6 (8), 1998–2016.
- Zeng, Q., Tang, C., Deng, L., Li, S., Liu, J., Wang, S., Shan, H., 2020. Differential diagnosis of COVID-19 pneumonia in cancer patients received radiotherapy. *Int. J. Med. Sci.* 17 (16), 2561.
- Zuo, H., 2020. Contribution of CT features in the diagnosis of COVID-19. *Can. Respir. J. J. Can. Thorac. Soc.* 10 (4), 1–16.