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Towards an ML-based semantic IoT for pandemic management: A survey of enabling technologies for COVID-19

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ABSTRACT

The connection between humans and digital technologies has been documented extensively in the past decades but needs to be evaluated through the current global pandemic. Artificial Intelligence(AI), with its two strands, Machine Learning (ML) and Semantic Reasoning, has proven to be a great solution to provide efficient ways to prevent, diagnose and limit the spread of COVID-19. IoT solutions have been widely proposed for COVID-19 disease monitoring, infection geolocation, and social applications. In this paper, we investigate the usage of the three technologies for handling the COVID-19 pandemic. For this purpose, we surveyed the existing ML applications and algorithms proposed during the pandemic to detect COVID-19 disease using symptom factors and image processing. The survey includes existing approaches including semantic technologies and IoT systems for COVID-19. Based on the survey result, we classified the main challenges and the solutions that could solve them. The study proposes a conceptual framework for pandemic management and discusses challenges and trends for future research.

1. Introduction

COVID-19 is an infectious disease provoked by a lately identified coronavirus SARS-CoV-2 strain, a kind of virus perceived to cause respiratory infections in humans. COVID-19 attacks the respiratory system and causes sicknesses such as cough, fever, fatigue, and breathlessness, as defined by the WHO organization [1]. The disease has spread quickly through countries and continents and has given rise to a global pandemic. It introduced many health challenges with economic, social, and political consequences and long–term impacts on our community. To fight the pandemic, WHO organization[2] has released a package of guidance, explanations, and related information. It also called for initiatives from all domains to support this humanitarian cause. The pandemic situation created an opportunity for scientists to develop Information and Communication Technology (ICT)-based solutions to cope with the pandemic. It is noticeable the emergence of systems for collecting and analyzing data, detecting and predicting COVID-19 disease, forecasting data, and developing mobile applications to assist the social life under lockdowns, such as online shopping and online meeting apps.

The high incidence of COVID-19 disease has resulted in an increase in data and information in this area. Machine Learning (ML) can help address the challenges that vast amounts of data pose; in fact, the more data we have, the better ML precision and accuracy will be. It processes and finds patterns in large data sets to enable decision-making. Most ML techniques were proposed in the literature to detect COVID-19 disease from a dataset of symptoms and vitals; others used the CT-scan and image processing techniques for the same objective. Also, predicting the number of cases was a typical application of different ML algorithms.

The huge amount of data presents many challenges in healthcare domain. The Researchers always try to tackle the heterogeneity of data formats and methods. The lack of a standard for denoting disease information is a significant challenge. It presents misunderstanding, confusion, and a limited automation process. One of the best practices to avoid confusion in recording and manipulating health information is to use new information tools

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[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-COVID-19#::text = symptoms

[2] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline

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0925-2312/

such as ontology. An ontology formally represents concepts and their relationships in a specific domain. Researchers worldwide have used ontologies since the late 1990s to support decision-making in various fields. The National Center for Biomedical Ontology has established a medical ontology database called Bioportal[3]. Most of the published ontologies in the field of coronavirus disease have been stored in this database.

On the other side, IoT sensor technologies and cloud Frameworks have played a significant role in fighting the pandemic. The IoT includes four components: sensors, networks, the cloud, and applications. The outbreak pushed their adoption as well as their implementation. Sensors have helped people overcome the outbreak by monitoring physical distancing, remote diagnosis, and treatment of patients. It has also floored the way to deliver essential medical supplies and medicine to isolated areas. IoT systems have been proposed for monitoring patients infected through devices and intertwined networks. Apart from healthcare, IoT played a role in other sectors such as Work from Home and E-Commerce during the pandemic.

Many research papers surveyed existing solutions for fighting COVID-19. Most of them focus on Machine Learning techniques, but none covers all the technologies, especially semantic technologies. However, semantic technologies have an essential role in solving data heterogeneity in healthcare domain; It also promotes knowledge sharing and semantics in a system. Through a systematic survey, our study aims to build shared awareness of the various projects and approaches adopted to fight the COVID-19 pandemic. The study proposes a conceptual framework for pandemic management and discusses challenges and trends for future research. More specifically, the objective of this paper is to answer the following research questions:

– (RQ1) What are the Machine Learning algorithms adopted for COVID-19 disease detection?
– (RQ2) To which sectors and applications have semantic technologies been applied to cope with the COVID-19 pandemic?
– (RQ3) What are the most relevant IoT solutions to cope with COVID-19 disease?
– (RQ4) Is it possible to combine the three leading technologies ML, semantic techniques, and IoT, to cope with epidemics such as COVID-19?

The state of the art in this study shows that neural networks are the most used techniques for disease detection using symptoms and image recognition. Conversely, most semantic approaches and ontologies have been applied for COVID-19 disease description and detection. Semantic and ML techniques could be used for the same objectives as IoT systems. But the literature shows that IoT solutions have been more adapted for monitoring purposes, maintaining social distancing, and geolocalized infections. It should be mentioned that in a situation such as pandemics, all technologies must cooperate and handle all aspects of the disease's effects. A system integrating ML, semantics, and IoT could be promoting to handle a pandemic.

The rest of the paper is organized as follows. Section 2 presents the knowledge gathering process adopted for this survey. Section 3 provides a detailed description of the concepts and algorithms of Machine Learning, Semantic Reasoning, and the Internet of Things. The findings of the state the art are presented in Section 4 as well as the challenges and solutions presented in each area. The results of the research and study are discussed in Section 5. Finally, Section 6 draws some conclusions and future research directions.

[3] https://bioportal.bioontology.org

2. Knowledge Gathering

The paper selection process consists of three steps; the first step is choosing the search engines to be used to search for relevant papers, the second step is selecting the keywords used in the search engine to answer the research questions, and the third step is to filter the resulting papers based on the relevance to answer the questions in the abstract.

In the first step, two search engines were used to gather all the required papers; Google scholar[4] and Bioportal[5]. For ontology-based papers, the National Center for Biomedical Ontology has established a medical ontology database called Bioportal. Most of the published ontologies in the field of coronavirus disease have been stored in this database. For all other papers, google scholar is used; google scholar is an academic search engine specialized in finding scholarly literature and academic resources.

In the second step to answer the research questions of this survey, the following keywords are used in the search engines "Ontologies for COVID-19", "Machine Learning techniques for COVID-19 detection", "Semantic approach for COVID-19", "IoT solutions for COVID-19", "Semantic IoT framework for COVID-19", and "ML-based IoT solution for COVID". In all search queries, the results were filtered to the recent articles published after 2000. We retrieved around 1130 papers concerning the techniques and technologies used to fight COVID-19.

In the third and the last step, the papers were selected based on their relevance to answering the research questions. Articles with a larger number of citations were assigned a higher priority during the filtering process of the literature. After the abstract examination, 99 papers were selected in this survey, resulting from papers at the end of this step.

Fig. 1 shows the distribution of the papers in the review by year. Naturally, all the selected papers were published after 2019, when the first cases of COVID-19 appeared, and the scientific community has an increasing interest in these topics. All the other papers are used for the purpose of the state of the art such as Machine Learning, Semantic technologies and Internet of Things.

3. Background

Artificial intelligence has two principal strands: Machine Learning and Semantic Reasoning. Arthur Samuel in 1959[1] described Machine Learning[2]3 as a "Field of study that gives computers the ability to learn without being explicitly programmed.".

Often ML models do not provide explicable outcomes, which is a crucial requirement in many critical domains such as health care. Semantic Web Technologies and Reasoning have been recognized under the umbrella term Explainable Artificial Intelligence (XAI)[4]. XAI was introduced when researchers showed that intelligent systems should explain the AI results via applied rules [5]. For instance, If a rule-based expert system rejects a credit card payment, it should explain the reasons for the unfavorable decision. ML and semantic techniques process huge volumes of data usually gathered from an IoT system. IoT system refers to a network of physical objects with sensors, processing ability, software and other technologies that connect and exchange data with other devices and systems over the Internet or other communications networks.

In this section, we review the AI strands and IoT that serve as a background of our research.

3.1. Machine Learning

Machine learning provides the data essential for a machine to train and modify appropriately when exposed to new data. This

[4] https://scholar.google.com/
[5] https://bioportal.bioontology.org

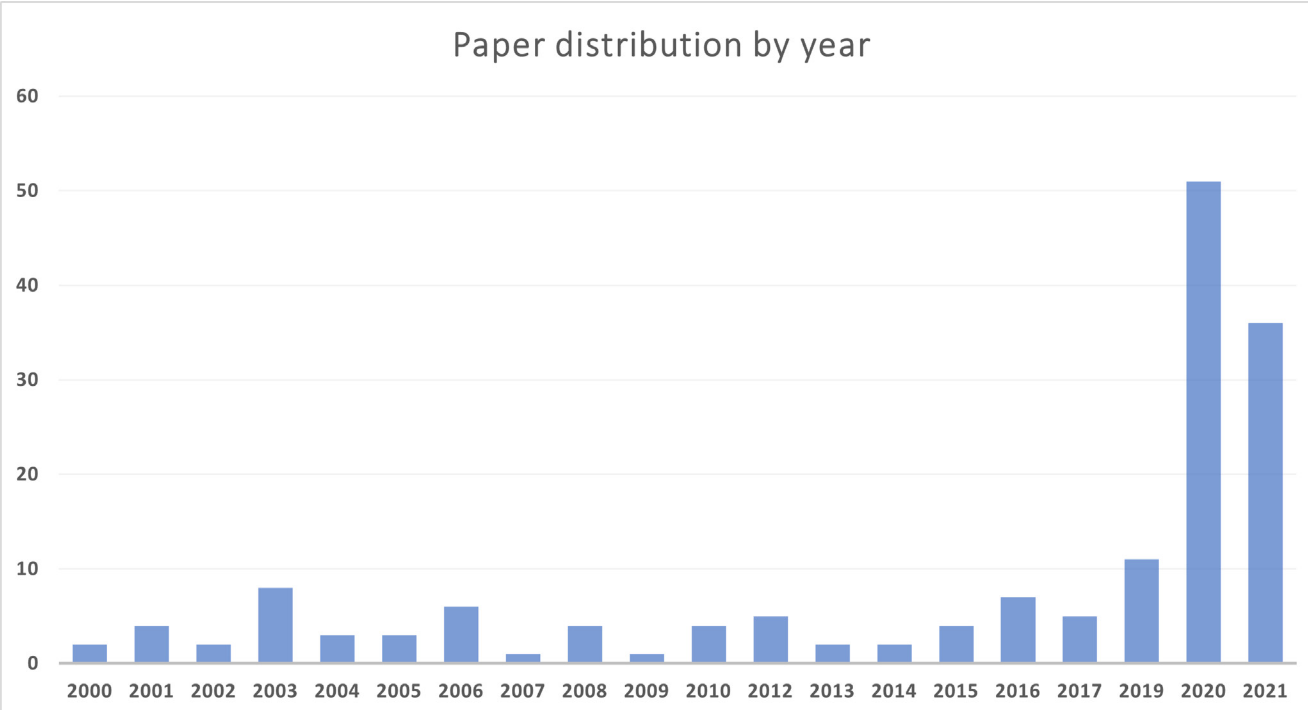

Fig. 1. Paper distribution in this review by year.

is known as "training". It focuses on extracting information from considerably large sets of data and then detects and identifies underlying patterns using various statistical measures to improve its ability to interpret new data and produce more effective results. Some parameters should be "tuned" at the intermediate level for better productivity. Machine Learning steps presented in Fig. 2 Show that extracting features and data collection take the maximum effort (80%) [6]. The other steps such as splitting the Data into training and testing sets, Model tuning, Evaluation and extracting Final Model take less effort to handle.

There are three types of machine learning, supervised, unsupervised, and reinforcement learning. The ML model makes decisions or predictions using past or labeled data in supervised learning. The unsupervised learning goal is to identify inconsistencies, patterns, or relationships within a set of input data. Reinforcement learning uses rewards, such as positive or negative feedback, to train the model.[7]

Supervised learning models are mostly used in healthcare and disease detection such as COVID-19. The most popular techniques for training supervised learning models are neural networks and decision trees. Both of these methods rely heavily on the data provided by the pre-determined classification [8].

Neural Network models have received considerable attention from research due to their immense potential in predictive and detection tasks. The main component of the Neural network model is a node, sometimes known as an artificial neuron, because it functions similarly to a human neuron. As presented in Fig. 3, the model can contain many nodes built upon multiple layers, with each node connecting to other nodes based on the desired output [9]. They are commonly utilized in the field of pattern recognition, which is regarded as one of the most challenging assignments for a computer to do. They provide a powerful tool to help clinical specialists model, analyze, and make sense of complex clinical data across a broad range of medical applications.

Neural Networks with multiple layers are referred to as Deep Learning or Deep Neural Networks (DNN). DNN is an important machine learning technique widely used in many areas. Compared to shallow Neural Networks (NNs), DNNs have better feature representations and the ability to adapt complex mappings [10] and to handle large amounts of data [11].

Since neural networks have witnessed tremendous growth over the last two decades, new algorithms coupled with increased computational power have enabled AI-driven applications to achieve near human-level performances. In [12], the authors present a new dimensionality reduction method that constructs a feature space spanned by its k intra-class nearest neighbors, which leads to a local projection on its nearest feature space. Numerical experiments showed the improved performance of the proposed method over the existing techniques. Other papers proposed to enhance the performance of the model by adding cost function on the layers of the Neural Network [13].

One of the key areas of research in neural networks has been evolutionary optimization methods that mimic the behavior in nature. In [14], the authors proposed a double optimization method based on particle swarm optimization. The proposed method was used to improve the performance of an ensemble of random vector functional link networks. In another optimization study [15], the authors solve the triple-level stochastic point location (SPL) problem using random walks. SPL deals with the problem of a learning mechanism (LM) determining the optimal point on the line when the only input it receives are stochastic signals about the direction in which it should move.

Neural networks have also made possible advances in discriminant analysis widely applied in medical studies. The goal of discriminant analysis is to build a classifier based on the assumption that the distribution of the attributes conditional on the target label is Gaussian. Several authors applied neural networks to solve the discriminant analysis problem. In particular, the authors in [16] used a Rayleigh–Ritz style method for large-scale discriminant analysis while the authors in [17] used regularization to obtain an efficient solution to the discriminant problem.

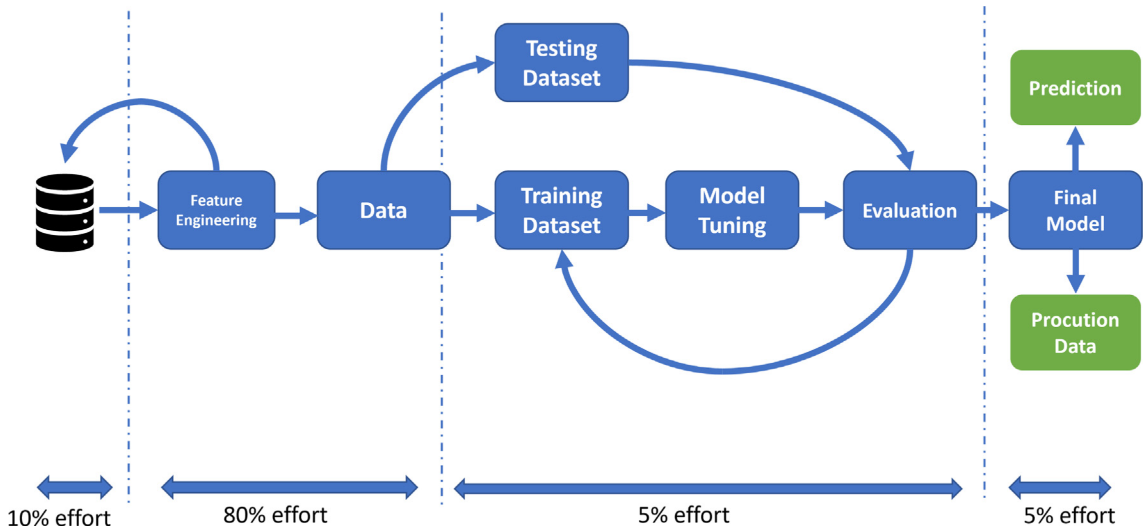

Fig. 2. Machine Learning steps.

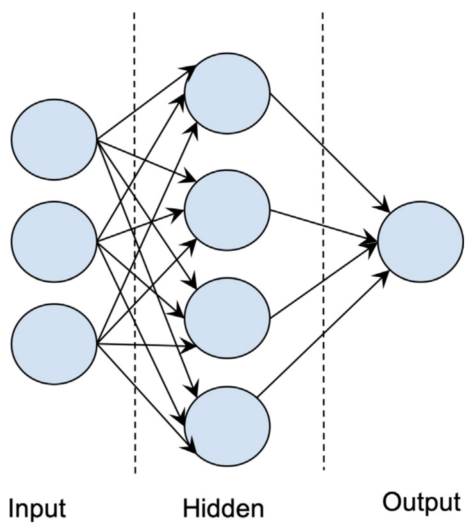

Fig. 3. Neural Network structure.

Feature selection is an essential step in ML to have accurate predictions. It is a way of selecting the subset of the most relevant features from the original features set by removing the redundant, irrelevant, or noisy. The researchers in recent years used feature extraction techniques to represent the original data in another projection feature space which empowers dominant inherent structure and reduces the dimension of original data. It is further used as a tool to overcome the problem of image segmentation in the existence of noise and intensity in homogeneity in medical images. Feature extraction techniques can be classified into supervised or non-supervised, linear, and nonlinear methods. The principal component analysis (PCA) is a representative linear feature extraction method. In the image domain, the PCA is performed as an eigenanalysis of the covariance matrix of the aligned shapes, which projects the original data into a low-dimensional subspace. Because the time taken for an eigenvector decomposition goes as the cube of the size of the matrix, this can give considerable savings [18–34].

The drawback in applying the traditional linear methods such as PCA and linear discriminant analysis depends on the Euclidean structure rather than the manifold geometry. Li et al. proposed a feature extraction method with local linear but global nonlinear transformation by integrating the class information with the local geometry [35]. The morphological scale-space decomposition based on multiscale spatial analysis represents a nonlinear method of scale-space feature extraction [36]. The advantage of this method is the preservation of scale-space causality, the localization of sharp-edges in the images [36–57], and the reconstruction of the original image from the scale-space decomposition.

Further, the researchers have made remarkable progress in image saliency feature extraction, and plenty of methods have been proposed, especially the deep learning-based methods, which have yielded a qualitative increase in performances. The Image saliency feature extraction methods can be stimulus-driven, which focuses on exploring low-level vision features by analyzing the pixel values and computing saliency values for each pixel; or task-driven, using supervised learning to achieve high performance.

The deep learning techniques have demonstrated the powerful ability in saliency features extraction. Some hierarchical deep networks for saliency detection were proposed, such as SuperCNN [58], and DHSNet [59]. In addition, the multi-scale or multi-context deep saliency network is proposed to learn more comprehensive features, such as deep contrast network, multi-context deep learning framework [60], multi-scale deep network [61], and network with short connections [62]. The symmetrical network is also introduced in saliency detection, such as the encoder-decoder fully convolutional networks [63].

3.2. Semantic Technologies

While machine learning results in a network of weighted links between inputs and outputs through intermediate layers of nodes, the semantic approach relies on explicit, human-understandable models of the concepts, relationships, and rules that constitute the selected knowledge domain. Three models have been used in intelligent environments: knowledge graphs, formal logic and ontologies.

knowledge graph is the representation of a knowledge base (KB) and its organization as a multi-domain graph, whose nodes represent entities of interest, combining different sources of vocabularies and data[64]. A knowledge graph representation comprises triples of the form < subject predicate object > which acquisition/creation can be automated[65] and represented with W3C Resource Description Framework (RDF) model[66].

Formal Logic. Richer representations, such as formal logic[67]68 (e.g., predicate calculus), are more complex and powerful and typically require human input in the acquisition/authoring process. Authors in [69] propose a logic-based approach for traumatic brain injuries detection. The process includes the Fuzzification step, where multiple inputs have to be mapped into functions using Eq. (1) in Fig. 4. The second step is the inference process, where logical rules are formed. The last step is defuzzification, where the outputs of the inference mechanism are output variables. The logic controller must convert its internal output variables into crisp values so that the existing system can use these variables. This step is done using Eq. (2) in Fig. 4.

$$\mu(x_i) = \begin{cases} \frac{x_i - a}{b - a} & a \le x_i \le b \\ 1, & b < x_i < c \\ \frac{d - x_i}{d - c}, & c \le x_i \le d \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$\mathrm{COG} = \frac{\sum_{x=a}^{b} \mu_A(x) \cdot x}{\sum_{x=a}^{b} \mu_A(x)} \quad (2)$$

Fig. 4. Fuzzification Eq. (1) DeFuzzification Eq. (2).

Ontologies and Semantic Modeling Modeling complex domains using ontologies have witnessed a remarkable adoption in intelligent environments [70] and health sector. The state of the art in this research focuses on the ontologies as a semantic modeling because it is the most commonly used in healthcare.

Ontology[72] is a formal representation of concepts and their relationship in a specific domain. One of the key motives behind developing ontologies is to provide semantic standards to improve the interchange of meaningful data. In computer science, ontologies are designed to model knowledge and facilitate a common understanding and communication between individuals and machines, making knowledge available for machine processing [73]. This approach leads to better analysis, resolves semantic heterogeneity between the different data sources in a domain, and reuses the domain knowledge. Fig. 5 illustrates the Ontology Learning cake[71], the first level in the cake includes the terms of a domain that refer to the minimum knowledge that can be represented. The more you go up in the cake, the more knowledge and semantic enrichment are defined to describe complex relations in a domain.

For an identified domain, an ontology defines the schema and the data semantically described by the defined schema called populated ontology. It stores knowledge about domain-specific entities, and those entities are classified as instances/ individuals of their ontological classes. It represents the domain knowledge using semantic links between entities which are characterized by a statement in the form of an RDF triple, Subject, Predicate, Object (SPO), where the predicate is a relationship between the other two entities. In healthcare[74], there is a need for efforts by physicians, researchers, and public health organizations to respond to infectious diseases; this requires to handle the challenge of the use of multiple, constantly changing data sources[75]. For instance, ontology has been designed in the medical domain to: improve the description of complex medical data[76], perform medical prescriptions[77], and overcome errors in diagnosis[78]79. An illustration of the ontology model is presented in Fig. 6.

In order to facilitate ontology development and application, many organizations or groups have developed various types of ontology tools, such as Apollo[81], OILEd[82], OntoEditor[83], Protégé[84][85], and WebODE[86]. Protégé remains the most adopted and popular ontology editing and modeling software developed by the Bioinformatics Research Center of Stanford University Medical College based on Java language.

Semantic Reasoning Semantic techniques goal[87] is to make systems intelligent by deducing new knowledge based on the available context data. Semantic Reasoning is the ability of a system "to make logical deductions from the information that is explicitly available." The inference rules are commonly specified using an ontology and a description logic language.

Reasoning with rules and ontologies[70] is the ability to infer information from existing data based on predefined rules/queries. The inference rules are commonly specified using an ontology language enabling automatic reasoning based on related conceptual domain assumptions. Semantic reasoning enriches a domain terminology by adding context, knowledge, and valuable insights, this is a form of Semantic AI. The SPARQL standard [88] is designed and endorsed by the W3C to express queries and semantic reasoning over ontologies.

W3C developed OWL[89] (Web Ontology Language) based on inheriting RDF grammar in order to expand the ability of ontology modeling and expression. OWL is an ontology language oriented to Semantic Web. OWL extends the modeling ability to describe Classes, Individuals, Properties, Property Characteristics, and Property Restrictions. OWL also defines the description class rules of Ontology Mapping, which enables ontology modeling to derive new classes or attributes in the form of Equivalence based on existing classes and attributes. In order to expand OWL's modeling and expression ability more freely. W3C defines SWRL[90] (Semantic Web Rule Language) based on RuleML[91]. SWRL extends the expressive power of OWL description language by describing Axioms in ontology modeling.

3.3. Internet of Things

IoT, the internet of things, is simply an interaction between the physical and digital world [92]. IoT has redefined how we live, work, and interact. IoT started in the early 80s when a group of students from Carnegie Mellon University designed a system to get their campus Coca-Cola vending machine to report on its contents to avoid the trouble of checking if the machine was out of Coke. Aside from the inventory report, they were also able to know whether newly loaded drinks were cold or not[93].

IoT devices are characterized[94] by their ability to collect data on their environments, communicate this data with other automated machines, and eventually, help the end-user gain information, solve a problem, or carry out a task. Depending on their practice, IoT is categorized into four main types[95,96]: consumer, organizational, industrial, and infrastructure applications.

The consumer IoT describes the utilization of personal devices, including smartphones, wearable technology, fashion products, and an increasing range of household appliances linked to the internet, continuously gathering and distributing information. IoT organizational[97] is widespread, mainly incorporating medical and facilities management settings. Specifically, IoT devices are used for remote monitoring and creating emergency notification systems for people, buildings, and assets.

Industrial IoT (IIoT) interface devices or machines, clouds, analytics, and people together to advance the execution and productivity of industrial processes. IIoT enables equipment monitoring, predictive maintenance, condition monitoring, error detection, and much more[98].

IoT appliances enable monitoring and controlling sustainable urban and rural infrastructures like bridges, railway tracks, and offshore wind farms. These technologies help the construction industry by cost-saving, time optimization, better quality workday, paperless workflow, and increased productivity[99].

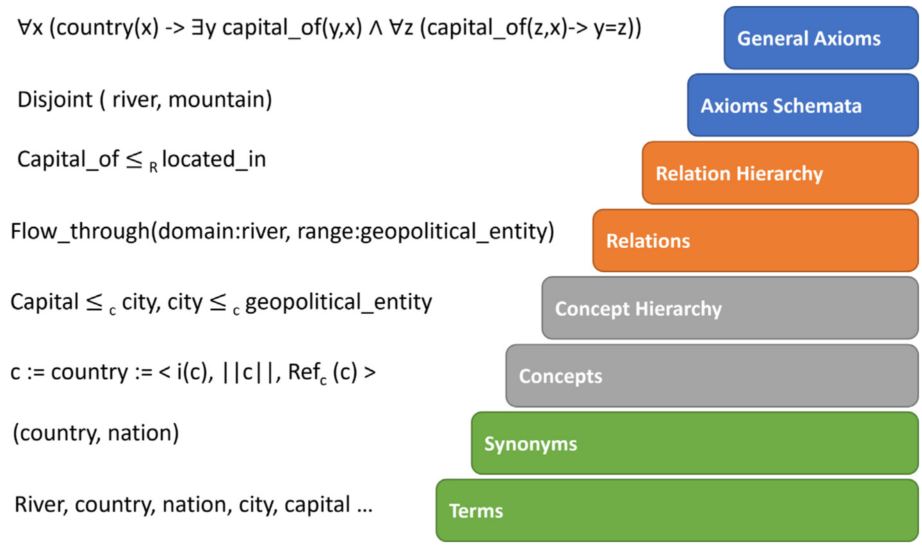

Fig. 5. Ontology learning cake[71].

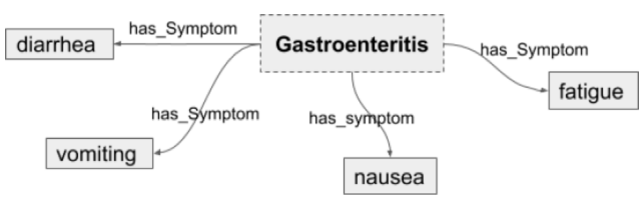

Fig. 6. The disease and symptoms ontological model for the gastroenteritis disease. [80].

4. Findings

In this section, we present the results and the findings of this research.

4.1. Machine Learning techniques for COVID-19

There is a large volume of research dedicated to machine learning applications for COVID-19 diagnosis. Detecting COVID-19 disease and differentiate it from normal flu was one of the main needs to support the medical staff. A literature review reveals two primary directions in current research: i) symptom-based diagnosis and ii) image-based diagnosis. In symptom-based diagnosis, patient symptoms such as temperature, headache, coughing, basic blood, and urine analysis are used to determine the presence of the infection. It has shown promising results that are less effective than image-based diagnostic approaches.

The medical imaging modalities such as chest X-ray (CXR) and computed tomography (CT) are mostly the common imagining that plays a significant role in confirming positive COVID-19 patients compared with RT-PCR results. The difference between the two modalities, CXR scanners produce 2-dimensional projection images of the patient's thorax, less in cost and patient preparation than the CT. On the other hand, the CT scans have a set of slices of a given organ without overlaying the different body structures in a more detailed structure. As presented in the literature[100], CT and CXR test has a great significance not only in diagnosing COVID-19 but also in monitoring disease progression and evaluating therapeutic effectiveness. CT and CXR findings include ground-glass opacity, consolidation, reticular pattern, air bronchogram, subpleural curvilinear line, and other abnormalities illustrated in Fig. 7. Ye et al. discussed the occurrence rate of different CT imaging results for COVID-19. The literature provides a reference for the following study of COVID-19, such as the segmentation of lesions and the corresponding classification[101].

The recent advances in computer vision have made this avenue of research particularly effective, with some studies achieving close to 100% accuracy in classifying patients based on lung imaging.

Despite the impressive results produced by many studies, machine learning algorithms are not yet ready for deployment due to limited test data and the absence of clinician input in developing detection methods. Some of the most used techniques are:

1. Support Vector Machine (or SVM) is a machine learning technique used for classification tasks. Briefly, SVM works by identifying the optimal decision boundary that separates data points from different groups (or classes), and then predicts the class of new observations based on this separation boundary.
2. Random forest (or RF) is a technique used in modeling predictions and behavior analysis and is built on decision trees. It contains many decision trees representing a distinct instance of the classification of data input into the random forest. The random forest technique considers the instances individually, taking the one with the majority of votes as the selected prediction.
3. A multilayer perceptron (MLP) is a feedforward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input and output layers. MLP uses backpropogation for training the network. MLP is a deep learning method.
4. Gradient Boosting Decision Trees (GBDT) is a machine learning algorithm, used for both classification and regression problems. It works on the principle that many weak learners(eg: shallow trees) can together make a more accurate predictor.

Symptom-based ML for COVID-19 disease detection. It has been shown that such primary symptoms as loss of smell and taste can accurately predict COVID-19 using machine learning techniques [103].The authors in [104] use data from emergency care clinics to identify COVID-19 cases. The study tested five machine learning algorithms - multilayer perceptron (MLP), random forest (RF), gradient boosting decision trees (GBDT), logistic regression, and support vector machines (SVM) - to predict the positive

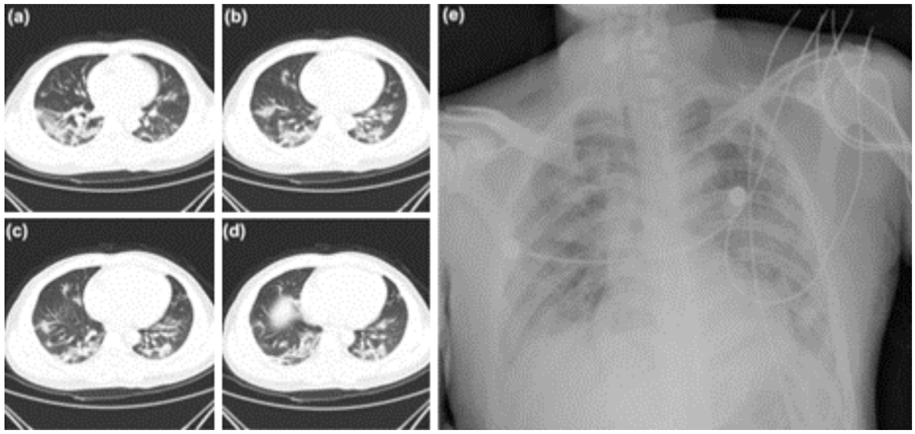

Fig. 7. a–d, CT scans of the chest with Bilateral focal consolidation, lobar consolidation and patchy consolidation lower lung. e, CXR shows Bilateral diffuse patchy and fuzzy shadows for the same patient after 5 days from CT[102].

patients based on their symptoms at the time of admission to the emergency clinic.

The study found that SVM produces the highest accuracy with an area under the receiver operating curve (AUC) 0.85. A more extensive study was conducted in [105] based on a dataset consisting of 8 basic clinical features. A gradient boosting algorithm was applied to identify positive cases; the results yielded an AUC of 0.90. As shown in [106], routine blood tests can also be used as a source of COVID-19 diagnosis. Their study of routine blood samples using the XGBoost algorithm produced an AUC of 0.97. The authors identified the five most helpful blood tests: MCHC, eosinophil count, albumin, INR, and prothrombin activity percentage. In [107], the authors considered only three primary criteria: age, gender, and nationality, to classify COVID-19 patients. A comparative study of four machine learning algorithms - MLP, RF, SVM, and GBDT - showed that the RF algorithm achieves the highest AUC of 0.63. Real-time monitoring of the symptoms of COVID-19 based on IoT technologies in conjunction with machine learning was proposed in [108]. On the other hand, certain studies have shown that symptom-based COVID-19 diagnosis may not be effective [109].

Image-based ML for COVID-19 disease detection. There are three main approaches in X-ray and CT image-based COVID-19 diagnostics using machine learning:

1. Hybrid approach using feature extraction together with a machine learning classifier.
2. Deep learning techniques.
3. Transfer learning together with a convolutional neural network.

Using the first approach, the authors in [110] used X-ray images to identify infected individuals. Their proposed method was based on first extracting features using Fractional Multichannel Exponent Moments and then using a special optimization technique to select the optimal features. The proposed method achieved accuracy rates of 96.09% and 98.09% on two tested datasets. Another fusion technique was proposed in [111] where the authors quantified CT images in terms of lung volume, lesion volume, nonlesion lung volume, and a fraction of nonlesion lung volume. The quantification was applied using U-Net models trained to segment lung and COVID-19 lesions in CT images. The extracted features were used with a random forest classifier to assess the disease severity. The results showed that the hybrid model achieved AUC 0.927. In [112] the authors use dimensionality reduction to obtain the optimal features from X-ray images which are used in the deep learning classifier to distinguish between COVID-19 and other types of pneumonia. Feature extraction along with several machine learning models including k-NN, SVM, random forest, and K-ELM was considered in [113]. The authors found that while k-NN and SVM achieve high accuracy in detecting positive cases of COVID-19, K-ELM achieves the highest overall accuracy. In[114], the authors employed transfer learning together with a convolutional neural network (CNN) to classify X-ray images as positive or negative for COVID-19.

Deep learning techniques have been widely used in the last years, promising results to accomplish medical imaging tasks rather than traditional techniques. Ai et al. investigate the correlation of chest CT and RT-PCR testing for coronavirus (COVID-19), presenting that in the clinical diagnosis of COVID-19, chest CT images have high sensitivity of 97% for the diagnosis and can be used as a primary tool for COVID-19 detection in epidemic area [115]. Silva et al. proposed an efficient deep learning technique based on mobile architecture. The proposed model extended efficient COVIDNet, by adding new blocks to efficient net B0 architecture guided by a voting-based approach and a cross-dataset analysis. The approach was evaluated using three experiments and the two largest public datasets, including a cross-dataset analysis. The accuracy drops from 87.68% to 56.16% due to the limitation of the diversity of datasets to be considered as a clinical option [116]. Santoch discussed the importance of the AI-driven tools and their appropriate train and test models using active learning in parallel with the experts to identify COVID-19. Moreover, the study discussed using multitudinal and multimodal data to support the decision-making process[117]. Hu et al. propose a supervised deep-learning strategy for detecting and classifying COVID-19 infection from CT images. The proposed method minimizes the manual labeling of CT images with a significantly accurate infection classification of COVID-19 from non-COVID-19 cases with accuracy 89.2% and sensitivity 88.6%[118]. Abass et al. adapted and validated pre-trained DeTraC-ResNet18 (Decompose, Transfer, and Compose) deep CNN architecture used for the classification of CXR images. A class decomposition layer is added to the pre-trained model. The added layer's functionality to sub-classes decomposition is treated as an independent class and then assembled to produce a final classification decision. DeTraC model achieved accuracy of 95.12% and 97.91% Sensitivity[119]. Lv et al. proposed that Cascade- ResNet50 and DenseNet169 deal with large input CXR images. The proposed model modified the pooling layer and added the attention mechanism to improve the efficiency of the classifier. The network accurately determined the type of pneumonia infection with 85.6% and 97.1% in the fine-grained classification of COVID-19[120]. Lin et al. introduced an adaptive attention network AANet to solve CXR images radiographic features extraction limitation. This limitation is due to the appearance of complex structures, such as widespread ground-glass opacities and diffuse reticular-nodular opacities. The model is based on learning feature representations, including shapes and scales of infected regions using the adaptive deformable ResNet; then, the attention-based encoder is applied to nonlocal model interactions to detect the lesion regions with complex shapes[121].

Oztruk et al. proposed a classifier based on the hand-crafted extraction features (grayscale, shape and texture, and symmetric features). Those features are reduced using PCA to be trained and classified using a support vector machine (SVM). The method was tested on 128 CXR images with 94.23% [122] accuracy. Soares et al. presented eXplanable deep learning classifier XDNN. The model is based on prototype-based learning, where the prototypes are training data samples as they represent focal points of valid generative modes. The model was tested against different classifiers ResNet, GoogleNet, VGG-x, AlexNet, Decision tree, and AdaBoost with accuracy reaching 97.31% [123]. Wang et al. introduced an open-source deep convolutional neural network COVID-Net designed specifically for detecting COVID-19 from CXR images, in addition to an open-access benchmark dataset COVIDx that includes 13,975 CXR images. COVID-Net shows accuracy 93.3% compared to other architectures VGG-19 and ResNet-50 [124]. Khan et al. presented a deep convolutional neural network model CoroNet based on Xception architecture. The model shows promising results in 4-class classification with sensitivity reach to 98.2% [125].

Transfer learning allows overcoming the issue of small training sets, common in COVID-19 datasets. Sara et.al use a pre-trained CNN on the ImageNet dataset to train on the new set of X-ray images. The results indicate that deep learning can detect the infection with the best accuracy, sensitivity, and specificity of 96.78%, 98.66%, and 96.46%, respectively. Transfer learning was also employed in [126], where the proposed architecture considered several pre-trained CNNs such as Xception, ResNet, and others to extract the relevant features from X-ray and CT images. Afterward, the extracted features were fed into several machine learning algorithms to identify the best method. The results showed the DenseNet121 feature extractor with bagging tree classifier achieved the best performance with 99% classification accuracy. In [127], Wang et.al considered five pre-trained deep learning models for transfer learning of X-ray images of COVID-19 cases. They found that the Xception pre-trained model and SVM achieve the optimal accuracy. Ensemble methods using CNN have also produced robust results [128]. Despite the high accuracy results, the current detection algorithms are not suitable for deployment to the small size of the test data which makes the accuracy results unreliable [129].

Transfer learning allows to overcome the issue of small training sets which is common in COVID-19 datasets. Sara et.al use a CNN that was pretrained on ImageNet dataset to train on the new set of X-ray images. The results indicate that deep learning has the ability to detect the infection with the best accuracy, sensitivity, and specificity of 96.78 the best performance with 99.

Challenges and solutions. This review shows the latest potential of deep learning models as a solution for CT and CXR COVID-19 images detection and classification. Table 1 shows the comparison for both the accuracy and sensitivity of various state-of-art of deep learning architectures on the COVID-19 chest imaging. As we can see, the difference among them is non-significant. It is coming from the following focal points:

1. Pre-processing stage either using handcraft or automatic techniques for feature extraction to improve the training and classification.
2. Using combined deep learning architectures for training and classifications.
3. The data sets are classified into 3 classes classification tasks:
   - 2-class (Non-COVID and COVID-19),
   - 3-class (Normal, COVID-19, Pneumomia viral), and
   - 4-class (Normal, COVID-19, Pneumomia viral, and Pneumomia bacterial).

Table 1
Average accuracy and sensitivity comparison for different state-of-art deep learning architectures implementation on COVID-19 datasets.

Architecture	Accuracy %	Sensitivity %
xDNN	97.4	95.5
ResNet	93.3	85.8
GoogleNet	93.4	85.4
VGG-x	92.5	83.7
AlexNet	94.4	94.7
Decision Tree	79.4	83.1
AdaBoost	95.2	96.7
COVID-Net	93.3	91.0
SqueezeNet	93.6	95.4
shrunken (SVM)	94.2	91.9
EfficientNet Voting	99.0	98.8

Most of the models consider 2-class and 3-class. The everyday challenges of using these models can be summarized as follows: (i) datasets in both diversity and scale. Consequently, the models need to be pre-trained and tested using a cross-dataset approach more realistically. (ii) The COVID-19 screening imaging techniques and protocols differ from one country to another, and environments differ significantly, which affects the generalization of deep learning solutions. (iii) The spread rate of COVID-19, deep learning solutions are expected to deal with cross-population, including pre-trained and testing models.

Another main challenge in diagnosing COVID-19 using machine learning algorithms is the lack of appropriate data. The issue of data availability is twofold: i) general lack of data and ii) skewed class distribution. The general lack of data stems primarily from patient medical data privacy issues. Collecting patient data requires passing through multiple legal hurdles, which either block access to data entirely or significantly delay its availability. Since machine learning algorithms need large amounts of data to learn meaningful patterns, the lack of data causes a significant impediment in the application of machine learning algorithms. For instance, the ImageNet dataset used in computer vision contains over 1 million training samples, while most COVID-19 X-ray images consist of only a few thousand images. As a result, the efficacy of machine learning methods is greatly diminished.

A significant issue with data is the skewed distribution of class labels. Since most individuals are healthy (negative), only a small portion of data is positively labeled. This creates an uneven class distribution which affects the learning ability of algorithms. Imbalanced data causes well-known problems, including classification bias [130]. One of the popular approaches for dealing with imbalanced data is through data sampling. Sampling involves balancing the dataset by artificially increasing the number of minority points [131,132]. In [133], the authors' employed SMOTE to balance the X-ray image data before analyzing it with a deep learning model. Nevertheless, it is impossible to completely eliminate the issues related to imbalanced data.

It is necessary to tackle the data availability problem to improve the future applications of machine learning for combating epidemics. This can be done by government agencies that can facilitate the collection and dissemination of clinical data to the research community. Rapid and easy access to data can drive research innovation. In addition, two possible techniques can be applied to deal with the lack of appropriate data. First, transfer learning can be used to mitigate the issue of a small training set. In this case, a classifier already trained on a large dataset can be employed for training on the new, smaller dataset. Second, sampling techniques can be utilized to balanced skewed class distributions.

4.2. Ontologies based solutions for COVID-19

COVID-19 pandemic has incited researchers' curiosity to discover this new disease, what it is, how to describe it, how it can be cured, and which vaccine formula will work well. Moreover, the spread of the disease across the continents required formal and international standards to be followed and respected by all countries to fight the spread. Also, developing any system to support COVID-19 pandemic requires the integration of data not only from the biology and medicine side, but also from public health, governments, geography, and social science. In this section we review the different ontologies that have been developed to support the COVID-19 pandemic.

Ontologies for COVID-19 disease detection. In the literature, many ontologies have been proposed to automate disease detection and especially COVID-19 disease. IDO[135] the Infectious Disease Ontology is a suite of interoperable ontology modules that aims to provide coverage of all aspects of the infectious disease domain, including biomedical research, clinical care, and public health. IDO Core covers entities relevant to contagious diseases generally and not specific infectious diseases associated with particular pathogens. The term 'Disease' is the heart of the IDO disease. Its core coverage ranges across biological scales (gene, cell, organ, organism, population), disciplinary perspectives (biological, clinical, epidemiological), and successive stages along the chain of infection (host, reservoir, vector, pathogen)[136].

In [137], authors presented two extensions of the IDO ontology to support the COVID19 case: CIDO and IDO-COVID-19. Based on the authors, these ontologies might assist in information-driven efforts to deal with the ongoing COVID-19 pandemic, accelerate data discovery in the early stages of future pandemics, and promote the reproducibility of infectious disease research.

CIDO[134] is an open-source biomedical ontology that supports coronavirus disease knowledge and data standardization, integration, sharing, and analysis. The design pattern of CIDO presented in Fig. 8 has been designed to logically represent and link the different components related to COVID-19, such as gene, location, process, vaccine, and drug. Fig. 1 represents many fundamental relations between COVID-19 disease concepts. Particularly, COVID-19 happens in the lung, and some genes in the lung cells would be susceptible up-or down-regulated in the cells of SARS-CoV-2-infected lungs. Such genes may function as gene markers and play significant roles in pathogenesis. In addition, the infected patient will present different phenotypes after manifesting the disease, and such phenotypes may be associated with other patient properties (e.g., biological sex, age) and the patient's gene profile.

The COVID-19 Infectious Disease Ontology IDO-COVID-19[138] is an extension of the CIDO ontology. It uses a term from the Virus Infectious Disease Ontology (VIDO)[139], and it introduces the term SARS-CoV-2 from the NCBITaxon[140], developing various qualities, dispositions, and material entities from the virus. In [137], the relationship between the three ontologies VIDO, CIDO, and IDO-COVID-19 is described as follows VIDO provides CIDO and IDO-COVID-19 the needed resources. For example, CIDO:subclinical coronavirus infection is a subclass-of VIDO:subclinical virus infection and IDO-COVID-19:subclinical SARS-CoV-2 infection is a subclass-of CIDO:subclinical coronavirus infection.

The COVID-19 ontology[141] comprises 2270 classes of concepts and 38 987 axioms representing major novel coronavirus

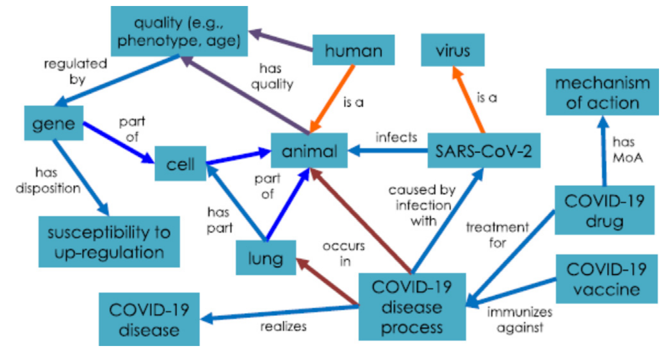

Fig. 8. The design pattern for CIDO[134].

(SARS-CoV-2) entities. The authors present the ontology as support to text mining frameworks and data description, linking, and harmonization in the context of COVID-19. The ontology describes the roles of molecular and cellular entities in virus-host interactions and the virus life cycle and a broad spectrum of medical and epidemiological concepts linked to COVID-19. The performance of the ontology has been tested on Medline and the COVID-19 corpus provided by the Allen Institute.

COVID-19OntologyInPatternMedicine ontology proposed by the authors in[142] relies on the works of Pattern Medicine(PM) and Generalized Biomedical Dynamics(GBMD). They focused on the scientific findings and the relations between the molecular and clinic levels to help the efforts against the pandemic outbreak. As per the authors' description, the ontology allows an improved understanding of medical conditions and makes medical decisions more integrated or systematic. The research proposes calculatable methods, rather than experience-based methods, usually used in the Traditional Information-Pieces-Accumulation Medicine (TIPAM).

LONGCOVID ontology proposed in [143] addresses the problem of the lack of standards and heterogeneity of methods applied to the COVID-19 disease. The authors in this research analyzed 303 articles published before April 29, 2021; they found that numerous publications describe the clinical signs of post-acute conditions of SARS-CoV-2 infection (PASC or "long COVID"). However, it is challenging to integrate all the information because of the heterogeneous methods used and the lack of standards. For instance, Patients and clinicians often use different terms to describe the same symptom or condition. The result of this research is mapping 287 unique clinical to Human Phenotype Ontology (HPO)[144] terms. Translating long COVID manifestations into computable HPO terms will improve the analysis, data capture, and classification of long COVID patients.

In[145], the authors present an ontology for preliminary detection of COVID-19 without the intervention of healthcare professionals. This ontology analyses the data from several sensors such as ECG sensor, Heart Rate sensor, Oxygen Saturation Sensor, temperature, and all conditions related to a patient. The author identified the SuspectedCase class updated by the "COVID-19" value when all conditions and symptoms specified by the Who organization have been found in a patient. A similar approach has been proposed in[146], but in this research, authors developed Semantic Web Rule Language (SWRL) to detect suspect cases in real-time.

Case-based reasoning (CBR) is used in[147] to detect new cases of COVID positives early by using an existing COVID-19 case database. It diagnoses patients of COVID-19 positives and negatives and predicts the pace with which COVID-19 spread will happen.

Ontologies for COVID-19 health care delivery. The COVID-19 pandemic has led to a dramatic loss of human life worldwide and presented an unprecedented challenge to public health, requiring a quick intervention from different specialties. Ontologies have been developed to describe and classify entities related to COVID-19 and primarily to provide a deep understanding of this disease[148] before proposing any drug or vaccine. Also, efforts have been made in this direction to offer ontologies related to drugs, vaccines, mental health, cardiology, and all aspects related to COVID-19.

DRUGS4COVID195[6] ontology defines medications and their relationships related to COVID-19. Some of the key classes of the ontology are drug, effect, disease, symptoms, disorder, chemical substance, etc. Another research in this direction is presented in [149]; the authors did a deep study on existing 1177 samples and built a model for formalizing drug indications. Drug formalization presents a big challenge as per the authors because of the different existing similar drugs. On the other side, efforts have been made towards vaccine development. For instance, in[150], an Ontology-based Precision Vaccinology approach has been proposed for Deep Mechanism Understanding and Precision Vaccine Development.

Based on the research done by the authors in [151], expressed genes in whole blood reveal genetic relationships between the COVID-19, chronic heart failure, and hypertensive diseases. In this research, the authors used the Gene ontology[152] for each of the diseases with COVID-19 has been discovered in order to understand better the relationship and find a gene pathway related to COVID-19.

CCOnto[153] is an integrated ontology that models the interactions between behavior and character states and traits in specific situations following the framework of the inter-disciplinary domain of Character Computing. This ontology has been proposed for anxiety detection during COVID-19. The work is the result of research cooperation between computer scientists and psychologists.

Finally, the C3HIS ontology has been proposed in[154] as a part of a web-based solution for the COVID-19 Crisis Health Care Information System. The authors suggested this ontology to help in managing the crisis in a hospital, prioritizing the COVID-19 services, taking into account the limited resources, professionals working with masks.

Ontologies for COVID-19 data collection and integration. COVID-19 has affected the worldwide economy due to the enforced lockdown that the public authorities have scheduled. The monitoring number of cases and mortality in each country was cumbersome. For that aim, many ontologies have been proposed to build datasets such as COVID-196. It is an ontology that consists of classes to enable the description of COVID-19 datasets in RDF. Some of the entities of this ontology are Dataset of the Johns Hopkins University. The WHO COVID-19 Rapid Version CRF [155] provides a semantic data model for the RAPID version (April 8, 2020) of the WHO's COVID-19 case record form. It aims at delivering semantic references to the questions and answers of the document.

CODO[156] The COVID-19 Ontology provides a model for the collection and analysis of data about the COVID-19 pandemic. It has been motivated by several data projection websites, WHO, the Indian government, and the Maryland government. It provides a standards-based vocabulary to be used by various entities such as government agencies, hospitals, researchers, data publishers, etc. CODO provides tracking of cases describing how the patient is thought to have been infected and potential contacts at risk due to their relationship with the infected individual. CODO also provides tracking of clinical tests, travel history, available resources, and actual need (e.g., ICU bed, invasive ventilators), trend study, and growth projections. Two other ontologies that come closest to CODO are kg-COVID-19[7] and Linked COVID-19 ontology[157]. KG hub ontology has been developed to produce a knowledge graph for COVID-19 and SARS-COV-2.). Linked COVID-19 Data uses RDF to present COVID-19 datasets from the European Centre for Disease Prevention and Control, John Hopkins University, and the Robert Koch-Institut. Also, the NASA Jet Propulsion Laboratory's COVID-19 Research Knowledge Graph[158] builds a knowledge graph from the COVID-19 Open Research Dataset (CORD-19). However, both of these ontologies have little semantic information in OWL and are dependent on a specific additional framework to utilize them.

The COVID-19 Surveillance Ontology[104] supports COVID-19 surveillance in primary care by facilitating the monitoring of COVID-19 cases and related respiratory conditions using data from multiple brands of computerized medical record systems. It is an application ontology designed to support surveillance in primary care. The main goal of this ontology is to support COVID-19 cases and related respiratory conditions using data from multiple brands of computerized medical record systems. This work is partially related to CODO. However, this ontology is designed as a taxonomy consisting of 32 classes such as education for COVID-19, exposure to COVID-19, definite and possible COVID-19, etc. This ontology does not consist of any properties, which reduces the semantic expressivity of the ontology.

The banking sector has seen a significant impact during the pandemic. Many researchers have been interested in describing and analyzing this impact. For instance, COVID19-IBO[159] provides semantic knowledge about the implications of the COVID-19 on the banking sector of India. It includes 159 classes with 77 properties complete, continuous, easily accessible, and readable. This knowledge is reusable according to the need of the user. To develop the COVID19-IBO ontology, data has been collected from different sources, articles, existing ontologies, databases, and reports related to COVID-19. A similar ontology has been proposed in[160].

COKPME[161] ontology is designed to be used by analysts for finding the relevant and precautionary standards that can be set in action for controlling the spread. It models information such as patient properties, the changes of the properties, which properties of patient confirm COVID positive, patients symptoms, their changes over time, and which sign is high in a particular region. It also models the treatment specifications.

COVID-19 ontology and natural language processing are used in [162] to detect fake news and inconsistencies between several reliable and not reliable medical sources by reasoning on the COVID-19 ontology.

In[163], the authors proposed a Semantic-Linked Data Ontologies for Indoor Navigation System in Response to COVID-19. The ontology allows to monitor social distancing and prevent transmission by checking the human density indoor. The proposed system is based on semantic descriptions of the components of navigation paths which, in turn, enable reasoning functionality.

Challenges and solutions. A summary of the previously discussed ontologies is presented in Table 2. In this tables, the solutions are categorized based on the usage application that varies between disease detection, drugs and vaccine description, crisis management, surveillance, patient and social distancing monitoring. We also specify the sector usage of these approaches.

One of the main challenges and motivations to use ontologies during the pandemic is the amount of data sources required to perform specific analysis. Due to privacy, medical institutions are restrained from sharing patients' data to be analyzed and fed to the applications for better assessments. The heterogeneity of the data

[6] https://github.com/oeg-upm/drugs4COVID19-kg

[7] https://github.com/Knowledge-Graph-Hub/kg-COVID-19

Table 2
A summary of Ontology-based Approaches proposed for COVID-19.

Ontology	Application	Sector
[135] 137 134 138 [141] [142] [143] [145] [146] [147]	Disease detection	Health
[148]	Drugs description	Health
[150]	Vaccine description	Health
[151]	Gene pathway	Health
[153]	Anxiety detection	Mental Health
[154]	Crisis management	Hospital
[155] [158]	Dataset	General
[156] [157] [161]	Data collection and analysis	Statistics
[104]	Surveillance	Smart homes/ hospitals
[159] [160]	Impact description	Banking
[162]	Fake news detection	Security
[163]	Social distancing monitoring	Indoor navigation

formats when shared is another challenge in this domain and makes it even more complex to integrate data and processes. Different sources must communicate together in a pandemic, government, hospitals, analysts, tech companies, etc. With a lack of standards and formalization of data, this information sharing is really complex to handle. Expert knowledge is required to describe data in a system, and the lack of expertise of the health professionals in IT constitutes a challenge. On the other side, validation tools necessitate the intervention of medical knowledge. That's why it takes time when thousands of terms are modeled and need to be evaluated and tested by the health sector and validate the correct usage.

The proposed solutions tackle several predefined challenges even though this effort is still incomplete and remains a future challenge for researchers and scientists.

4.3. IoT and Cloud-based frameworks for COVID-19

The Internet of Things (IoT) have proliferated over the past decade. They continue to evolve in terms of size and complexity, offering various devices to support a wide variety of applications. Cloud computing is a term for hosted computing services provided to customers over the Internet. IoT and cloud computing complement each other to improve IoT service overall. IoT and cloud computing integration improve interactions with intelligent objects by providing access from multiple places, boosting data exchange efficiency, and increasing storage and processing capacity [164]. Moreover, It is much easier to monitor patients from a considerable distance with the usage of IoT and Cloud services, especially for those who find it challenging to access healthcare institutions.

There are a lot of research and development efforts in IoT during the COVID pandemic. In this section, the focus is on Cloud-assisted IoT applications and the challenges related to their usage.

The cloud computing and IoT ecosystem are presented in Fig. 9. The devices of all forms in IoT have the ability to connect to the cloud. The connected devices proactively generate data stored in the cloud in various formats. The data is available then to the analysis through the cloud services. Finally, it will be available to the users to be consumed in its final application.

Four main components in any COVID-19 IoT application are essential in order to have effective monitoring and control over patients, to have superior track and trace COVID-19 mechanisms, to have enhanced COVID-19 diagnosis, and to have cost-effective COVID-19 pandemic management[166]:

1. **Hardware and sensors**: The first component addresses the hardware and sensors; they can be found in many forms. The primary condition is to be equipped with network connection capability in order to share data. Popular hardware and sensors used in most of the applications are smartphones, computers, cameras, geolocation chips, drones[167], RFID tags, and wearable devices [168].
2. **Software**: The second component is the software that is used to manage the hardware to collect and send data properly. The software can be in any form of an application running on top of a smartphone or virtual communication tool. The software can address issues such as energy efficiency, optimized data collection, optimized usage of smartphone hardware [169].
3. **Data Analysis**: As the number of sensors deployed grows, so does the amount of data collected, necessitating the adoption of data filtration and big data management systems. Machine learning and artificial intelligence, in general, are becoming increasingly popular in the analysis and decision-making of sensory data.
4. **Regulation**: There are a lot of ethical issues that need to be addressed and regulated in the IoT ecosystem. This component addresses regulations of problems related to the security and privacy of the users when their data is being used without violating users privacy[170]. Another example is regulating the usage of the hardware to prevent COVID-19 contamination.

A perfect example that uses all the components in the COVID-19 IoT application is presented [171]. The authors propose an application to monitor and manage potentially infected patients of COVID-19 using wearable devices that track patients' location. The sensors placed on the body are connected to the IoT Cloud, where data is analyzed and processed to define the patient's health state. The proposed system has three layers: Wearable IoT sensor layer, cloud layer, and android software layer. Another example of IoT cloud-based application for COVID-19 detection is presented in [172]. The authors detect fever symptoms using special sensors; the data is transmitted to the cloud to alert the monitoring manager user. When the collected data reaches a critical level, automatic action will be taken to resolve the situation.

Authors in [173] identified 281 empirical articles. They concluded that 28 various forms of technologies have been used, ranging from computers to artificial intelligence, 8 different populations of users are using these technologies, primarily medical professionals, 32 generalized types of activities are involved, including providing health services remotely, analyzing data, and communicating, and 35 various effects have been observed, such as improved patient outcomes, continued education, and decreased outbreak impact.

Real-time detection of COVID-19 using IoT devices emerged during the pandemic. The proposed system in [169,174] uses an Internet of Things (IoT) framework to collect real-time symptom data from users. Its purpose is to detect suspected coronavirus cases early, monitor the treatment response of those who have already recovered from the virus, and learn more about its nature by collecting and analyzing relevant data. The applications of real-time COVID-19 detection are endless, in [175] proposed installing different IoT devices in hospitals, banks, grocery stores, and other public places. These devices work completely hands-free to prevent contamination. These devices scan each person's temperature, look for a face mask, listen to his coughs, and ask verbal questions concerning symptoms. If a person is suspected of having the virus, he is offered appropriate advice. Preventive advice is given to those that are clear.

One of the most used applications that evolved in the IoT domain during the COVID pandemic is enforcing social distancing. To prevent COVID-19 outbreaks, most countries applied protective

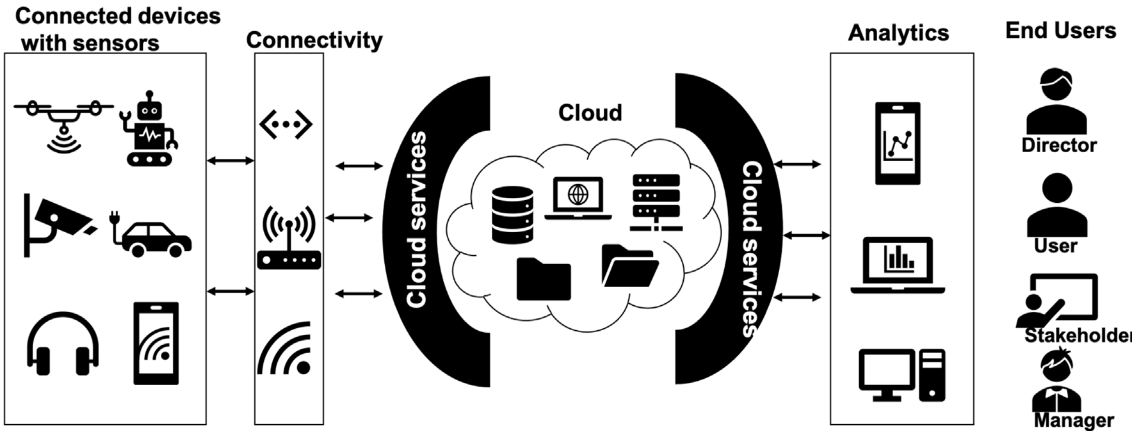

Fig. 9. The Cloud computing an IoT ecosystem. Adapted from [165].

measures, social distancing, curfew, and lockdown. Moreover, some countries went further by monitoring their people to ensure they respected the measures. Drones with loudspeakers are used in Spain and other nations to advise people to stay at home [167]176.

Robotics have been used at hospitals to deliver meals, transport medical samples, spray disinfectants, clean, dispense hand sanitizers, and perform diagnosis and conduct thermal imaging. In some severely infected areas, drones have come to the rescue by transporting medical equipment and patient samples. Drones equipped with image processing algorithms and facial recognition are used to recognize infected cases or broadcast warnings to the citizens not to step out of their homes during the lockdown. In Thailand, Two ABB robots are part of an innovative AI-Immunizer system being used to help speed up the development of an effective vaccine that can be used to fight the spread of the COVID-19 virus. Developed as part of a collaboration between the Faculty of Engineering at Thailand's Mahidol University and the Institute of Molecular Biosciences, the system uses ABB's IRB 1100 and YuMi®collaborative dual-arm robots to assist with key tasks involved in vaccine testing and development[8]. Multi-robot collaboration may be managed in a decentralized manner using blockchain technology, which improves their interaction by allowing them to share information, representation, goals, and trust. [177].

Other IoT applications to enforce social distancing use connected devices to host virtual remote conferences and online learning. A network of smart devices with installed programs like Zoom, cloud meetings, Google meet, Microsoft Teams, and others are used to impose the work-from-home culture. [178]. We buy almost everything online and have it delivered to our door, including groceries and prescriptions sometimes. The importance of technology in our lives has never been more apparent. Although many technologies and platforms existed pre-pandemic, their volume to our daily living increased exponentially during the pandemic. It is likely to continue in many areas post-pandemic[179]. A color-coding health rating system for daily tracking was used. The system assigns three color codes: green, yellow, and red to the people based on their travel and medical histories. Only those who are green color-coded with a designated QR code are allowed in public. A similar solution called the Tawakkalna application was proven successful in fighting the COVID-19 pandemic in the KSA[180]. The app offers a personalized profile displaying the person's status (affected, vaccinated, or no history of infection). Like color codes, CCTV cameras have also been installed at different locations to ensure that quarantines do not step out.

Certain IoT apps are utilizing blockchain, an emerging technology that allows for data storage in the form of immutable blocks. These apps are designed to address a critical issue: the absence of integration of reliable data sources. One of the key advantages of utilizing blockchain-enabled apps, according to experts, is blockchain's capacity to validate continuously changing data. This functionality could be quite useful in dealing with the quickly rising COVID-19 problem. [181] One application that uses blockchain is MiPasa[9], which is a data streaming platform that allows individuals, authorities, and hospitals to share verified health and location data.

Virtual reality is a valuable platform for Automation, Architecture, Gas, oil industries, and education[182]. Virtual reality was used to disseminate awareness and educate on how to fight against COVID-19. Researchers[183] found that VR is beneficial for remote sites when exploring telemedicine, planning, treatment, and controlling infections by providing proper awareness regarding this disease. VR technology develops a platform to reduce the face-to-face interaction of doctors with infected COVID-19 patients. Through live video streaming, it helps to improve surveillance systems on the ongoing situation. In 2020, 32% of consumers used AR for shopping. The augmented reality and virtual reality market for the retail industry alone are expected to reach $2,094.08 billion by 2027, witnessing market growth at a rate of 68.5% in the forecast period of 2020 to 2027[10].

Challenges and solutions. While the aforementioned applications are beneficial, they do not come without flaws and restrictions. Privacy issues and the public's objection to sharing data are major concerns. Stakeholders are concerned about the security and privacy of data acquired when IoT implementations are established. Many countries encourage building applications that respect the privacy of the people. In Canada, an application, "ABTraceTogether" was created that enables people to exchange non-identifying information with other users via Bluetooth; other users will not have access to any individually identifying information. The app exchanges Bluetooth-enabled secure encrypted encounter logs (or "handshakes") with nearby phones running the same app in the Bluetooth range. These handshakes are anonymized and encrypted and do not reveal any identity or other personal information. [184].

Other countries such as the UK, France, and the USA have similar applications to track the patients and alert them respecting privacy and personal information. However, other countries such as

[8] https://new.abb.com/news/detail/76818/cstmr-abb-robots-help-accelerate-COVID-19-vaccine-development-in-thailand

[9] https://www.ibm.com/blogs/blockchain/2020/03/mipasa-project-and-ibm-blockchain-team-on-open-data-platform-to-support-COVID-19-response/

[10] https://www.forbes.com/sites/forbestechcouncil/2021/09/14/augmented-and-virtual-reality-after-COVID-19/?sh = 6a99965c2d97

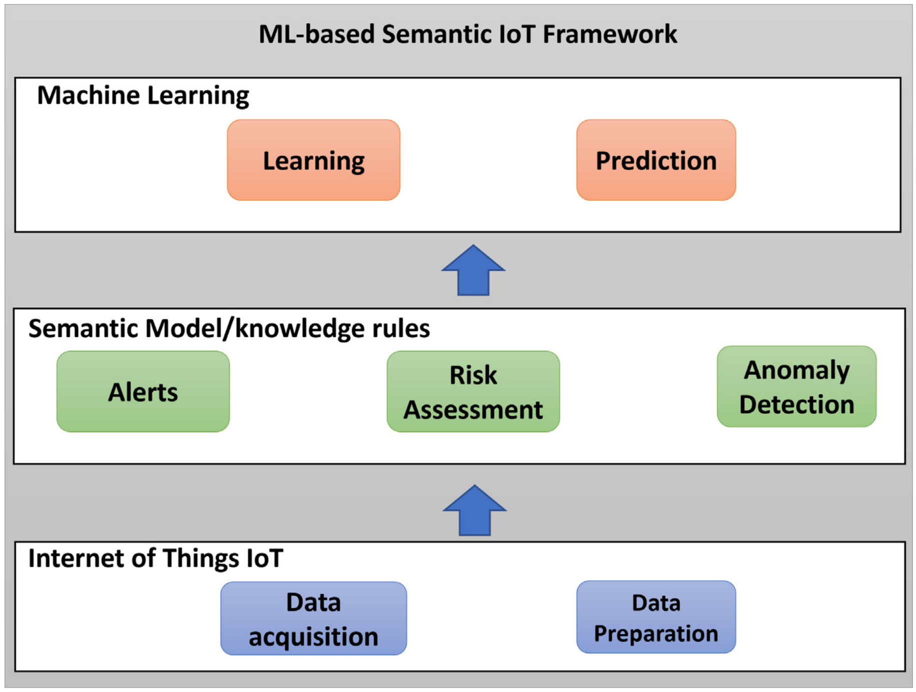

Fig. 10. The ML-Based semantic IoT Framework.

China track people's symptoms, location, and issues real-time individual health status through applications that have potential privacy issues. [185].

The various IoT implementation methodologies have been influenced by the policies surrounding the requirement for social distancing on IoT collecting data. COVID-19's contagious nature has prompted IoT administrators to seek numerous effective and ethical sensor deployment methods. Secure IoT device communication methods are also expected to preserve user privacy and maintain system integrity [166].

5. Discussion

In this section, we discuss the literature review findings regarding the research questions we presented in the introduction.

(RQ1) What are the Machine Learning techniques used for COVID-19 disease detection? In order to define the ML techniques addressed by researchers to detect COVID-19, we classified them into two categories symptoms-based and Image-based. Our study shows that SVM, RF, MLP, and GBDT have been mostly used for symptoms-based COVID-19 detection, and deep learning technique, especially CNN, has been mostly adopted.

(RQ2) To which sectors and applications have semantic technologies been applied to cope with the COVID-19 pandemic? We found that ontologies and semantic technologies have been widely used to describe the COVID-19 disease concepts, symptoms, drugs, vaccines, and gene descriptions. We classified the approaches into three categories: Ontologies for disease detection based on symptoms, Ontologies for healthcare delivery such as drugs and treatments, and Ontologies for data collection and integration. We have also defined the different applications: Disease detection, drugs, vaccine, gene, anxiety, crisis, surveillance, data collection, fake news, and social distancing. Moreover, the study categorizes eight sectors implementing ontologies for COVID-19 Health, mental health, statistics, smart homes, banking, and indoor security navigation.

(RQ3) What are the most relevant IoT solutions to cope with COVID-19 disease? IoT solutions have been widely adopted for monitoring purposes and real-time applications for collecting and gathering data in a hospital, supermarkets, banks, and malls. Also, IoT systems have been used to implement sensors and monitor vitals and COVID-19 symptoms. Virtual reality was used to disseminate awareness and educate on how to fight against COVID-19. Cameras and drones have been mostly used for social distancing.

(RQ4) Is it possible to combine the three leading technologies ML, semantic techniques, and IoT, to cope with epidemics such as COVID-19? Our study shows that many applications and systems have been proposed to cope with the COVID-19 pandemic, each using different technology and having a different objective. On the other side, many existing solutions proposed hybrid approaches combining IoT and semantic technologies such as in [186,187]; their main objective is to tackle the challenge of the integration and harmonization of the huge data produced by IoT systems. Other research studies[188,189,?] show that Combining ML and semantic in an IoT environment is necessary to ensure predictive analytic and preventive personalized health services.

Based on that, we found that future research directions must investigate a Hybrid approach including the three components of ML, semantic, and IoT techniques for an effective pandemic management such as COVID-19. Fig. 10 shows an ML-Based semantic IoT conceptual Framework. The IoT component is responsible for data collection from health and geolocation sensors, prepares data and sends it to the semantic component. The semantic component receives the data from the IoT sensors, annotates it and saves it in the ontological model. Semantic rules can be applied to infer and generate alerts, risks and anomalies. Finally, the ML component learns and predicts useful information from the data received from semantic component.

6. Conclusion

As the world undergoes an ongoing battle against the deadly COVID-19 virus, we see rapid evolution in technologies towards monitoring and reduction of the virus spread. This article reviewed several technologies being adopted in combating COVID-19.

The major contributions of this study were the analysis of several machine learning models available in the literature, their classification; and their challenges/solutions have been discussed. The study shows that increased availability of high-quality, and reliable data will improve the containment and monitoring of a fast-spreading virus-like COVID-19. Additionally, in the image-based COVID-19 detection domain different innovative approaches were used. These approaches concentrated on extracting features from images using ML algorithms. They also discussed how data could be used with the different ML algorithms. The deep learning models were presented as one of the best solutions to detect COVID-19 disease. The common challenges to applying deep learning to medical images (CT and CXR) were also presented. Moreover, a comprehensive study of the ontologies developed over COVID-19 disease was presented. The ontologies help describe the COVID-19 data with formal and international standards, improving the interchange of meaningful COVID-19 data, hence better-integrating data collected from different areas. Therefore data can be better used for COVID-19 detection. Furthermore, this work provides a comprehensive illustration of the IoT and cloud-based emerging services. Privacy issues of the data collection were discussed. During the pandemic, IoT enabled better clinical judgments and improved COVID-19.

Finally, this work provides a new conceptual approach combining ML, semantic and IoT techniques for an efficient pandemic management such as COVID-19. Public authorities such as government could use the hybrid framework to monitor all the aspects of the pandemic. Future work includes a complete study and description of this hybrid approach.

Data availability

No data was used for the research described in the article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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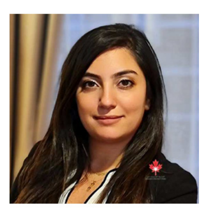

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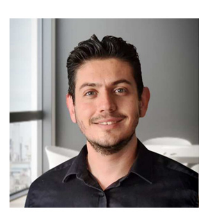

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