Blockchain Assisted Disease Identification of COVID-19 Patients with the Help of IDA-DNN Classifier

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Abstract
Globally, millions of people were affected by the Corona-virus disease-2019 (COVID-19) causing loads of deaths. Most COVID-19 affected people recover in a few spans of weeks. However, certain people even those with a milder variant of the disease persist in experiencing symptoms subsequent to their initial recuperation. Here, a novel Block-Chain (BC)-assisted optimized deep learning algorithm, explicitly improved dragonfly algorithm based Deep Neural Network (IDA-DNN), is proposed for detecting the different diseases of the COVID-19 patients. Initially, the input data of the COVID-19 recovered patients are gathered centered on their post symptoms and their data is amassed as a BC for rendering security to the patient’s data. After that, the disease identification of the patient’s data is performed with the aid of system training. The training includes ’4’ disparate datasets for data collection, and then, performs preprocessing, Feature Extraction (FE), Feature Reduction (FR), along with classification utilizing ID-DNN on the gathered inputted data. The IDA-DNN classifies ’2’ classes (presence of disease and absence of disease) for every type of data. The proposed method’s outcomes are examined as well as contrasted with the other prevailing techniques to corroborate that the proposed IDA-DNN detects the COVID-19 more efficiently.

Keywords COVID-19 · Disease identification · Deep Neural Network (DNN) · Blockchain · Data security · Post symptoms · Lung damage · Heart failure after COVID-19 · COVID-19 issues

1 Introduction
COVID-19 [1] is caused by means of a newly found enveloped RNA β-coronavirus labeled severe acute respiratory syndromes corona-virus 2 (SARS-CoV-2) [2]. It is a swiftly spreading infectious disease of the human respiratory system that occurred recently creating a colossal dysfunction of disparate activities worldwide [3]. On 11th March 2020, the Worlds Health Organizations (WHO) officially announced COVID-19 as pandemics
Since then, it has spread rapidly with numerous cases, and associated deaths still augmented on an everyday basis [5]. Usually, the symptoms of this virus are fever, cough, as well as dyspnea but can encompass serious consequences, say pneumonia, multiple organ failure, and also even death [6].

The sars-Cov-2 infection affects the lungs first and rapidly moves towards the vascular system with platelet alterations, blood clotting abnormalities, and associates with a higher occurrence of cardiovascular events, venous thromboembolisms (VTE), liver disease, together with kidney injury particularly in seriously ill patients [7]. SARS-CoV-2 is an atherosclerotic cardiovascular virus that can cause a tension pneumothorax and has long-term repercussions in some people. SARS-CoV-2 is spread through contact with infected fluids such as salivary and respiratory droplets, as well as respiratory secretions, that are produced when an infected individual breathes, coughs, speaks, or plays. Common comorbidities of COVID-19 are hypertension and cardiovascular disease. The individuals exposed to SARS-CoV-2 are often robustly associated with the hazard of hospitalization along with death [8]. Additionally, it also has high phenotypic similarity with other clinical conditions, like respiratory viral infections, lung contusions, as well as pulmonary complications subsequent to sepsis [9]. COVID-19 is a multi-system infection, which largely infects the respiration system; however, it also causes cardiovascular disease [10] endothelialitis, systemic inflammation, and also thrombosis [11]. Patients affected by the SARS-CoV-2 are prone to death whilst building up rigorous pneumonia, ARDS, or multiple organ failure, pulmonary edema, neurologic complications [12]. Aimed at mitigating the HC system’s burden, the disease’s effectual diagnosis is required whilst rendering the finest potential care to patients [13]. Numerous researches exhibit that a re-positive examination aimed at the virus utilizing the RT-PCR in patients recovered is extremely common [14]. SARS-CoV-2 is exceptionally contagious with the Ro’s transmission rate (effectual reproductions number) = 2.2 (1.4–3.9) [15]. COVID-19, the infectious viral disease stimulates a serious burden on the body and leaves the patients to suffer as of the symptoms extensively past recovery. Numerous infection possibilities occur post COVID. The complication includes Acute Kidney Injury (AKI), neurological disease, viral, and bacterial infections, blood clots, and organ failure in various organs, cardiovascular disease, pneumonia, and also trouble to breathe. Using a human–machine cooperative design technique, a neural network-based architecture has been designed for the identification of COVID-19 instances from CXR pictures. Blockchain technology has the potential to enhance clinical study information management by lowering planning permission bottlenecks and streamlining communication between multiple stakeholders in the supply chain, among other things. Data collection and analysis, which may involve the gathering of substantial quantities of personal or non-sensitive data for computerized disease surveillance and overall health monitoring, might include acquisition of vast volumes of personal or non-sensitive information. This has far-reaching consequences further than the original disaster management [16–18].

Recent science and technology have given much helpful contribution towards implementing the states’ novel policies in this unknown as well as unpredictable procedure [19]. In generating a platform aimed at effectively administrating the COVID-19 pandemic, BC Technology (BT) plays a crucial part. BC comprises numerous potential use cases, which can aid in handling the present pandemic crisis. It is utilized to simplify the clinical examination methods aimed at fundraising activities, transparently track donations, raise public awareness, and also functions as a dependable data tracker, and vaccines as well as drugs [20]. BC aids in establishing treatments quickly as they will permit for speedy data processing, hence facilitating early symptoms detection before they reach the epidemics’ level. Lately, numerous deep learning-centred AI systems are built to distinguish the COVID-19
and the Community-Attained Pneumonia (CAP) or the other viral pneumonia and also to quantify the infection areas [21]. Utmost deep learning advancements on medical imaging have taken place with the Convolutional Neural Network’s (CNN) introduction [22]. The image features are extracted utilizing the CNN. After that, the features are harmonized with the patient’s report aimed at identifying the complications. This work proffers a new BC-aided optimized Deep Neural Network, termed IDA-DNN to detect the various diseases encountered by the recovered COVID-19 patients, which assists the doctor to render earlier treatment for the patients.

This paper’s draft structure is arranged as: Sect. 2 surveys the associated works concerning the proposed protocol; Sect. 3 renders the proposed work’s detailed elucidation; Sect. 4 reveals the experiential outcome; Sect. 5 exhibits the conclusion.

### 2 Related Work

This section has broadly investigated the lately published papers for various difficulties faced by the COVID-19 recovered patients. Wang et al. [23] examined the treatment and incidence of AKI on pediatric patients affected by COVID-19 in Wuhan Children’s Hospital in the early phase of the pandemic and possible mechanisms of AKI related to SARS-CoV-2 were discussed. By means of extracting the data as of electronic medical records, they have performed an observational review of kidney association in confirmed pediatric COVID-19 cases, as of January 24 to March 20, 2020. Amongst the 238 patients confirmed with COVID-19, only 3 were seriously sick and an Intensive Cares Unit (ICU) admission was required. Seriously sick children affected by COVID-19 were formulating AKI. An inflammatory storm as well as complement-mediated injury might underlie AKI formulation in COVID-19 affected children. This study had supported the implantation of Plasma Exchanges (PE) and Continuous Kidney Replacements Therapy (CKRT) in the critically ill patient’s management with AKI. Still, kidney histomorphology on COVID-19 affected children was not proved.

Kunal et al. [24] investigated the complications of Cardio-Vascular (CV) and their effects on symptomatic patients (COVID-19). It was a single-centers observational investigation amongst those patients. A frequently encountered complication in patients (COVID-19) was acute cardiac injury and also it was associated with increased mortality. Cardiac biomarkers were employed for hazard stratification of seriously ill patients for identifying those who need intense monitoring. Presently, advocated treatment regimens encompassed QT-interval prolonging drugs, say HCQ and azithromycin, which called for strict cardiac monitoring particularly in seriously ill patients. Yet, the correct mechanism concerning CV contribution was still uncertain.

Chen et al. [25] investigated the occurrence of thromboembolisms in mild/moderate on COVID-19 cases. As of June 11 to July 8, 2020, twenty-three patients with mild/modest COVID-19 pneumonia allowed to have a CTPA (CT pulmonary angio-graphy) with CTV (CT venography) scans aimed at the lung and also extremity veins. 19 patients (i.e. 82.6%) had VTE, mostly distal limbs thrombosis. With the assistance of DUS, one of the VTE was monitored, the other VTE were negative by DUS. By means of CTV screening aimed at DVT, it was observed that the occurrence of thrombosis in mild to moderate COVID-19 patients was increased to 82.6% (19/23). Though they failed to treat these patients with anti-coagulant therapy, this study highlighted the requirement of providing
much consideration to the thromboembolism risk in COVID-19. They reported a comparatively little, single-center investigation.

Dujardin et al. [26] studied Venous Thromboembolisms (VTE), which was a common difficulty in critically sick COVID-19 patients and was connected by mortality. In retrospective cohort analysis, 127 patients (adult) with definite infection (COVID-19) were in ICU. With the aid of ultrasound or else computed tomography scans, VTE was diagnosed. The prominent CRP as well as D-dimer had a highly positive predictive value intended for VTE in seriously ill patients. A constraint of this investigation was that the CT imaging was carried out on clinical doubt and not as a standard of care, probably causing under-diagnosis of PE.

Lopez-Mendez et al. [27] investigated the occurrence of liver steatosis and fibrosis of COVID-19 patients and their connection with clinical outcomes. The abnormalities in the Liver Functions Tests (LFT) were detailed in up to 50% patients (COVID-19); metabolic co-morbidities were linked with poorer results. A retrospective examination on patients (hospitalized) was performed. The risk aimed at liver steatosis was assessed by HSI > 36, and also the risk for superior liver fibrosis via APRI > 1.0, NAFLD FS > 0.675, and/or FIB-4 > 3.25. 96.8% of patients (COVID-19) had a minimum of one abnormal LFT. The occurrence of steatosis along with important liver fibrosis was higher in patients (COVID-19) but wasn’t connected with clinical results. The disadvantages comprise the retrospective model, the appraisal of liver fibrosis by non-invasive designs.

Mamta et al. [28] discussed the computation time of the ABSE system is controlled in the future framework by performing the computationally heavy operations of a conventional ABSE system on the public blockchain. As a result, in a conventional cloud-based cyber-physical systems, the suggested technique is suited for online storing of medical information.

Pashchenko et al., [29] produces the findings of a study covering the transformation experiences of 26 working groups from of the country’s biggest IT businesses, device manufacturers, and high-tech businesses with good domestic development practices are presented in this section.

Nguyen et al., [30] presents a safe intrusion detection system for CPS in the healthcare industry using blockchain-based data transfer and a categorization methodology. The described approach uses sensing devices to collect data, and employs a deep belief network (DBN) method to identify intrusions.

Abdur Rahman et al., [31] describes their perspectives in creating and building a COVID-19 case identification and tracking structure based on neural networks (DNNs), such as the use of live face detection to recognise supportive living trying to distance practises from images captured, as well as face mask identification from images captured.

Esposito et al., [32] investigated the smart city ecosystem’s decentralized administration of security-related knowledge is addressed. By employing block chain to maintain a global picture of the security protocols inside the network and incorporating it into the FIWARE framework, this provides a novel approach for distributed administration of identification and authorizing regulations.

Masud et al. [33], introduces a lighter weight and physiologically secure authentication process and secret key incorporation procedure that employs Physical Unclonable Functions (PUF) to allow connected devices to validate the doctor’s validity and sensor prior to actually having established a session key to safeguard IoMT systems from threats such as verification, personal privacy, truthfulness, and confidentiality.

Sedik et al., [17] discussed about both X-ray and CT pictures, as well as a composite dataset containing all kinds of digital, are used to test the suggested machine learning
methods. In order to evaluate the proposed methodologies, COVID-19 and pneumonia picture classifications are also categorized. In certain situations, they reached 100 percent accuracy and a 100 percent F1 measure.

3 Proposed Methodology

Here, a new BC aided IDA-DNN has been proposed aimed at finding the covid-19 health problems utilizing the covid-19 patients’ post symptoms. IDA is a set of optimization methods which can be used to solve a variety of problems, such as improving weight values from an ANN. DA was inspired by the static or dynamic stages of dragonfly activity in reality, which are analogous to the meta-heuristic’s cycles. A dragonfly’s term period resembles the exploitative phase in meta-heuristics, which comprises a large group of dragonflies travel in one path. The dynamic response, on the other hand, is comparable to the evaluation stage, during which dragonflies process information and fly over various places in search of native species [34]. At first, the diverse COVID-19 patients’ post symptoms are gathered as input. The data amassed via the patients are saved as a BC-centred on the trusted authority certificated issued by the health admin which can offer privacy to the patient’s health records. Next, the patient’s health problems or diseases are predicted that is executed by carrying out training on the famous datasets. The datasets are preprocessed, extracted feature, dimensionality reduced; at last, categorized aimed at finding disease prevalent in the patients. Entirely ‘4’ diverse diseases kinds are detected by the proposed technique, like lung, kidney, liver, and heart disease. The proposed method’s architecture is provided as:

3.1 Identification of Symptoms

The proposed method’s 1st pace is the detection of the COVID-19 recovered patients’ post symptoms. The COVID-19 recovered patients possess health problems still past 2 months treatment, 3 months treatment, and 6 months treatment for COVID-19. The health problems concerning the recovered COVID-19 patients are kidney disease, lung damage, heart disease, liver failure, et cetera. A necessity exists aimed at finding these hurdles at a former pace and rendering a prevention treatment for those patients via doctors, which aids to save the people as of severe injury. Aimed at finding the diverse diseases’ problem levels centred on the patients’ post symptoms, this work proposes a BC aided classification design. Respiratory symptoms such as fever, coughing, and difficulty breathing are signs and symptoms. Inflammation can spread to pneumonia, acute respiratory syndrome, Sars syndrome, and even demise in the most severe cases. Cough, difficulty breathing or shortness of breath, fever, shivering, muscle soreness, stiff neck, and new lack of smell or taste were among the most prevalent COVID-19 symptoms.

Elderly people and people comprising numerous severe health conditions are most probable to face persistent COVID-19 symptoms; however, even young or healthy people may as well feel ill for weeks to months past the infection. The main general symptoms and signs which remain over-time comprise fatigue, breathing obscurity, joint pain, chest pain, and also cough. Additionally, long-term symptoms and signs may involve loss of taste, brain fog and/or smell, rash or hair loss, as well as sleeping problems. As of these symptoms, the classification method detects whether a patient comprises a severe problem level in a few organ or not. The COVID-19 patients’ generally affected body parts are the heart,
kidney, lung, and liver. Every disease comprises its own symptoms on the patient. Initially, the patient’s symptoms are organized underneath the disease type; then, the related testing methods are recommended to the patients aimed at finding the problem’s level. Rapid diagnostic tests (RDT), Molecular tests, lateral flow antigen test, Serological tests using blood samples are some of the testing methods [35].

3.2 Sorting of Symptoms

This stage finds the patients’ symptoms and then sorts the patient’s symptoms by the disease type. If the patient possesses rigorous chest as well as joint pain, then there occurs a chance to possess heart failure in the future. Consequently, people having chest pain symptoms appear beneath the heart disease kind. Similarly, grounded on the patient’s symptoms, the disease type is detected which signifies the chances of possessing a particular disease in the upcoming future. Table 1 exhibits the post symptoms of the COVID-19 patients possessing the possibility of comprising a diverse disease.

3.3 Data Collection

Past sorting the symptoms under the disease type, it is essential to gather the data as of the patients aimed at finding the disease’s problem level. The data can differ aimed at every disease type. The proposed technique finds the ‘4’ main diseases faced by COVID-19 patients, like kidney, lung, liver, as well as heart failure. To detect these diseases, the system has to go through training with the classification algorithm’s aid. During training, data as of diverse datasets are gathered as of explicitly available sites. Additional processes, like pre-processing, FE, dimensionality reduction, along with categorization, are executed on the inputted data aimed at detecting the diseases. It surpasses the model approach, which used a quadratic interpolation to enlarge each sliced to meet the needed dimensions of the channel’s input nodes. It also incorporates a strong pre-processing strategy that comprises lung identification and picture normalization. Convolutional neural networks (CNN) were utilized to extract characteristics from X-ray pictures, which were then merged to build the classification model using CNN retraining [36]. The training classifier outcome involves the diseases’ categorizing output (presence of disease—normal and absence of disease—abnormal) for the patients. Centred on the training system, the COVID-19 patient’s real-time disease prediction has been executed, which assists the doctors in offering an early prevention method to the patients.

Nevertheless, ‘2’ major focuses exist in real-time prediction, which are: data ownership and data security. Lack of a secured structure in the sensitive medical records presently

| Table 1 | Post symptoms related to diseases for COVID-19 patients |
|------------------------------------------------------|--------------------------------------------------------|
| Post symptoms                                       | Possibility of having the disease                      |
| Chest pain, joint pain, shortness of breath, and Fast or pounding heartbeat | Heart Failure or heart attack                           |
| Shortness of breath, cough                          | Lung disease                                           |
| Rash or itchy skin, fatigue, loss of smell or taste | Liver problems                                         |
| Shortness of breath, fatigue, tiredness             | Kidney failure                                         |
leads to data breaches with serious consequences. Consequently, the BC concept is utilized here which reduces the accessibility and security of the patient’s medical records.

### 3.4 Trusted Authority Based Blockchain

The works established a BC system centred on the certificate authority aimed at Medical Records’ (MRs’) effectual storage as well as sharing that offers effective data security and privacy. The system concentrates on ‘3’ kinds of users: Physicians or doctors, Patients, and Health Admin. Health Admin does registration tasks for the patients as well as doctors. A single global block chain technology can be the foundation for a great ideas electronic medical record, providing a secure development medium means of processing and maintaining patient data in a logical step that is publicly accessible in true by anybody in the healthcare network operator chain. The addresses of a medical chart are recorded on the very same blockchain held by network participants. All individuals are recognized by one-of-a-kind certificates issued by local digital certificates who operate together in a network channel. When transferring data, we choose a trustworthy authorities system to preserve a patient confidentiality [37].

- **Registration of doctor and patient** The health admin registers the patient and doctor utilizing their related information. The health admin must confirm that only the valid users must be registered in their association. After registration, the health admin sends the patients’ registered information to the application (user app) established via the hospital admin which issue a Trusted Authority Certificate (TAC) to the patient aimed at each authorized registered patient. Centred on the TAC, the user app creates a private/public key pair and a symmetric patient key and then offers this to the patient. Now, the patient can utilize this identity material aimed at logging in into the system. This procedure is also the same for the doctor. To get access to the system, the doctor is provided with the ID and private key.

- **Transaction of medical data** The patient can share their patient key utilizing that doctor’s public key, whilst a patient wants to share their data with a doctor. A doctor can request this key as of the patient and whilst offered the doctor can access the patients’ MRs and can put in novel records.

- **Data Storing using BlockChain** Whilst the data is transmitted as of the patient, it is stored as a BC which comprises the BCs with every block of transaction information in the key-value pair as well as database form that saves the value of all the last committed transactions as per the particular key. If the whole patient data is stored as a blockchain that will degrade the BC system’s performance. Consequently, the BC holds the transactional information along with the database holds data values. Past this technology, these real-time patient data’s disease detection is found utilizing the training outcomes’ aid. The section below elucidates the proposed methodology’s brief paces of training aimed at every disease.

### 3.5 Feature Extraction of Lung Failure Detection

The gray-level coocurrence matrices generated this feature extraction technique, which uses term frequency inverse document stats to analyses structural relevant information on how well the visual system processes images. The spatial dependency matrix creates a visual pattern that can be used to decode the damaged image. The values are well dispersed
near to the matrices diagonally when picture features are not deteriorated. Otherwise, depending on the level of structural degeneration, different patterns emerge. As a result, the SIM matrix structure of a healthy lung differs significantly from that of a fibrotic lung. A healthy lung’s components are compact, scant, and also have a lot of variety. The 1st disease pondered here is the lung disease. The collection of patients’ chest CT images prevalent in the dataset are gathered to find whether the recovered COVID-19 patient possess lung disease or not. The procedures done on the dataset’s images involve filtering, FE, as well as classification. This section describes just the filtering and FE executed by the proposed method aimed at lung disease identification. To eliminate the noise prevalent in the inputted images, this work utilizes the standard median filter, which ejects the salt and pepper noises and creates an improved image. Next, the LRELU grounded DCNN is employed aimed at the filtered image’s FE.

A DCNN is the feed-forward neural network. A biologically inspired machine learning algorithm is the feedforward neural net. It is made up of a huge set of common neuron-like processors that are arranged in strata. Each component in a level is linked to all the components in the level before it. A classic CNN’s architecture encompasses a Convolutionals Layer (CL), Pooling Layer (PL), and Fully Connected Layer (FCL). In general, CNN attempts to build numerous filters that are able to extract hidden features via the inputted data’s layer-by-layer convolution as well as pooling. At last, these abstract features are combined via the FCL; an Activation Function (AF) is utilized for resolving the classification issue. In a neural network, an activation function specifies how well the weighting factor of the inputs is turned into an outputs from a circuit or node in a layer. The activation is based on a set of rules or a set of thresholds. The activation function’s primary objective is to develop non-linearity into the network. Nevertheless, the AF employed in DCNN is the ReLU, which experiences a possible demerit that the units can never activate after the gradients reach zero that means the weights are not updated at back-propagation aimed at activations in that area. This may generate dead neurons, which never get activated. Hence, aimed at overcoming demerits like that, this work utilizes the Shaped-ReLU (SReLU) in the ReLU’s place, which can study both the convex and non-convex functions, mimicking the numerous function forms by the ‘2’ fundamental laws, like the Webner-Fechner law and the Stevens law, in neural sciences and psychophysics. Weber’s law is a psychological rule that quantifies the impression of changes in a new activity and has been around for a long time. According to the principle, the only detectable modification in a stimulus is a consistent proportion of the original stimulus. According to Steven Law, a neurophysiological relationship exists in which the emotional size of an experience is proportionate to the intensity of the condition that causes it. The SReLU is studied together with the entire deep network’s training via back-propagation. It upgrades the DCNN’s classification accuracy. This pace is termed SReLU-DCNN aimed at the lung disease FE (Fig. 1). Figure 2 exhibits the SReLU-DCNN’s structure. Every layer’s steps are elucidated as,

**Convolutional Layer** CNN’s main building block is the CL. This layer extracts the features as of the inputted image and creates the outputted feature maps utilizing the AF. The CL develops the data’s output by computing the scalar product betwixt the region linked to the inputs as well as their weights.

$$\Phi = I_L \ast A_f(\tilde{W}_{vl_b}(I_L)_{pls})$$

(1)
Here $I_L$ signifies the inputted pre-processed lung image; $A_f(\bullet)$ implies the proposed SReLU’s AF; $\left(\overrightarrow{W}_{vls}(I_L)_{pls}\right)$ signifies every pixel values’ weight vector prevalent in the inputted image. The SReLU is equated as

$$A_f(p_i) = \begin{cases} t_{pmr}^i + d_{pmr}^i (p_i - t_{pmr}^i), & p_i > t_{pmr}^i \\ t_{learn}^i + d_{learn}^i (p_i - t_{learn}^i), & p_i \leq t_{pmr}^i \end{cases}$$

(2)
Here, \( \{ t_i^{pmr}, t_i^{learn}, d_i^{pmr}, d_i^{learn} \} \) signifies the ‘4’ learnable parameters utilized for designing an individual SReLU’s activation unit. The subscript \( i \) signifies that the permission is offered to the SReLU aimed at a change in diverse channels.

**Pooling Layer** The PL is utilized for decrementing the number of CNN parameters. It aids in decrement computation and also assists in making the feature detectors much invariant to their location in the input. Another component of a CNN is the pooling layer. Its purpose is to gradually shrink the representation’s model complexity in order to minimize the number of variables and computations in the system. Each feature vector is treated separately by the pooling layer and Max pooling is the most popular method of pooling.

**Fully Connected Layer** At last, the feature maps attained by the numerous convolutional and PLs’ computations pondered as the FCL’s inputs that then compute the image’s final output vector (extracted features) in an FCL that has links with all activations in the preceding layer.

### 3.6 Feature Extraction for the Detection of Other Diseases

The other diseases detected by the proposed classifier are heart, kidney, and liver failure. To find every disease, diverse widely available datasets are employed. The procedures done by the proposed protocol are the same aimed at these three diseases. The proposed work performs preprocessing, FE, and FR before classifying the input data. The preprocessing of the dataset includes missing value imputation, removal of redundant data, and data normalization. The missing values in the dataset can be removed by computing the mean/median of the non-missing values on a column and then replacing the missing values within each column separately and independently from the others. After that, the data size is reduced by eradicating unrelated or redundant attributes. Finally, data normalization is done to obtain the dataset with the same data range. Mins-Max normalization technique is employed in the proposed work for normalizing the data. This transforms a feature value or data value \( F_{val} \) to normalized data that fits in the gamut \([0.1]\). The data normalization in the dataset \( (N_{\vec{r}})_{ds} \) is signified utilizing the Eq. (3),

\[
(N_{\vec{r}})_{F}^{ds} = \left( \left( \frac{F_{val} - [F_{min.val}]_{ds}}{[F_{max.val}]_{ds} - [F_{min.val}]_{ds}} \right) * (1 - 0) + 0 \right)
\]

(3)

Here, \([F_{max.val}]_{ds}\) and \([F_{min.val}]_{ds}\) signifies the feature data’s maximal as well as minimal values. Normalizing the data tries to offer all features an equivalent weight. The features are extracted as of the disease datasets as the preprocessing procedures are executed. Table 2 exhibits the kidney, heart, as well as liver dataset’s extracted features.

### 3.7 Feature Reduction and Classification

Past extracting of the data features as of the diverse datasets, the features extracted are decremented utilizing the Principal Components Analysis (PCA). Principal Component Analysis, or PCA, is a dimensionality-reduction approach for reducing the dimensions of large amounts of data by converting a large collection of factors into a shorter one that retains the relevant information in the huge array. It accomplishes this by generating new negatively correlated variables that optimize variation in a sequential manner. Dimensionality reduction regarding techniques aimed at lessening the number of inputted variables.
in training the data. Whilst handling higher-dimensional data, it is a lot helpful in decrement the dimensionality by presenting the data into a lower-dimensional sub-space that grabs the data’s "essence"; it upgrades the categorization accuracy. Past the PCA’s application, IDA-NN is utilized aimed at the disease’s classification. DNN comprises a particular level of intricacy and more than ‘2’ layers: an inputted layer, an outputted layer, and one Hidden Layer (HL) in betwixt them. The neural network’s weight learning is the parameter system’s heavy complex optimizing procedure; it falls easily into local minimum; also its convergence speed is much slower. Aimed at increasing the DNN’s computational speed as well as prediction accuracy, the optimization method, like IDA, is utilized that encompasses an immense ability aimed at global searching, and speedy converging is employed efficiently to define the weights regarding diverse connections. This IDA centred weight optimization aimed at DNN is termed IDA-DNN. Figure 3 exhibits IDA-DNN’s structure,

**Step 1** Input the diverse dataset’s reduced features.

**Step 2** Create the weight values aimed at every inputted data which is fed into the inputted layer, and then assign it to the HL neurons and the outputted layer neurons. Sustain the weight aimed at the inputted layer’s every neuron. The weight values aimed at every inputted data are optimally chosen utilizing the IDA.

**Step 3** Enumerate the HLs’ output (HLs 1, 2, 3, 4) utilizing the Eqs. (4), (5), (6) & (7). The proposed method utilizes ‘4’ HLs aimed at finding the disease prevalent in the patients.

\[
[H]_{i}^{fst} = [B]_{i}^{fst} + \sum_{i=1}^{N} F_{val}^{i} [W]_{i}^{fst}
\]

\[
[H]_{i}^{snd} = [B]_{i}^{snd} + \sum_{i=1}^{N} [H]_{i}^{fst} [W]_{i}^{snd}
\]

Table 2 Disease datasets and their extracted features

| Disease dataset | Extracted features |
|-----------------|--------------------|
| Heart           | Age, sex, type of chest pain (4 values), resting blood pressure, serum cholesterol in mg/dl, fasting blood sugar > 120 mg/dl, exercise-induced angina, resting electro-cardiographic outcomes (values 0, 1, 2), maximum heart rate, old peak = ST depression induced by means of exercise relative to rest, the slope of the peak exercise ST segment, number of major vessels (0–3) coloured by means of flouroscopy, and thal: 3 = normal; 6 = fixed defect; 7 = reversible defect |
| Liver           | Age, sex, BMI, Hemoglobin (g/l), ALP (IU/l), RBC \( (10^6 /μl) \), WBC \( (10^3 /μl) \), INR, Na (mmol/l), ALP (IU/l), Total Bilirubin (mg/dl), Direct Bilirubin (mg/dl), GGTP (IU/l), Na (mmol/l), K (mmol/l), Cholesterol (mg/dl), Total Protein (g/dl), Albumin (g/dl), Albumin and Globulin Ratio (%), Alkaline Phosphotase, Sgpt Alamine, Sgot Aspartate, PT prothrombin time(S), AST, along with ALT |
| Kidney          | Age, sex, blood pressure, specific gravity, albumin, sugar, blood urea, CKD stage, anemia, pedal edema, coronary artery disease, diabetes mellitus, hypertension, white blood cell count, red blood cell count, potassium, sodium, serum creatinine, hemoglobin, sugar, pus cell, pus cell clumps, blood glucose random, bacteria, as well as packed cell volume |
Here, $[H]_{fst}, [H]_{snd}, [H]_{trd}, [H]_{fr}$ signifies the first, second, third, and fourth HLs’ output; $[B]_{fst}, [B]_{snd}, [B]_{trd}, [B]_{fr}$ implies the first, second, third, and fourth HLs’ bias values; $[W]_{fst}, [W]_{snd}, [W]_{trd}, [W]_{fr}$ symbolizes the weight values of HLs: 1, 2, 3 & 4; $F_{val}$ implies the inputted data values (reduced features) as of the dataset.

**Step 4** Identify the final output; the last HL is multiplied with the weight of the same HL’s output that is articulated as,

$$[O]_{DNN}^{i} = [B]_{fie}^{i} + \sum_{i=1}^{N} [H]_{i}^{trd}[W]_{i}^{fie}$$  \hspace{1cm} (8)

Here, $[W]_{fie}^{i}$ signifies the optimized weight of the final HL’s output; $[B]_{fie}^{i}$ implies the bias value of the final HL’s output; $[O]_{DNN}^{i}$ symbolizes the outputted unit which specifies whether the patient possesses a disease or not.

**Step 5** Estimate the outputted layer’s activation function ($\hat{A}_{f}^{n}$); then formulate the learning error as:

$$\hat{A}_{f}^{n} = \frac{1}{1 + e^{-[O]_{DNN}^{i}}}$$  \hspace{1cm} (9)

---

**Fig. 3** Structure of DNN
\[
\hat{L}_e = \sum_{i=1}^{N} (\hat{T}_i^{DNN} - [O]_i^{DNN})
\]  

Here, \(\hat{L}_e\) implies the error rate; \(\hat{T}_i^{DNN}\) signifies the target outputted value; \([O]_i^{DNN}\) symbolizes the actual outputted value.

Utilizing IDA, the weight optimization done by DNN is elucidated below.

### 3.8 DNN Optimization using IDA

The Dragonfly Algorithm’s (DA) core idea comes as of the Dragonflies’ (DFs’) dynamic and static swarming behaviours. The ‘2’ necessary stages of optimization: (i) exploration, and (ii) exploitation, are build by designing the DFs’ social interaction during navigating, searching foods, and evading enemies whilst executing dynamical or statistical swarming. ‘2’ cases occur in which swarm intelligence appears in DFs: feeding as well as migration. Feeding is designed as a statistical swarm in optimization; migration is designed as a dynamical swarm. Swarms possess ‘3’ definite behaviours: (i) separation, (ii) alignment, as well as (iii) cohesion. The separation concept means: an individual prevalent in the swarm evades the static collision with his/her neighbour. The alignment specifies the speed at which the agents coordinate with the adjacent individuals. At last, the cohesion concept exhibits the individuals’ tendencies towards the herd’s centre. ‘2’ added behaviours are summed up to these ‘3’ fundamental behaviours in the DA: travelling towards food and also evading the enemy. The reason aimed at adding up these behaviours to the DA is that every swarm’s core intention is to live.

Nevertheless, with the fundamental DA’s use, the solution outcomes often are not similar to reality underneath the case of a huge number of variables. Albeit the right solutions as of the convergence to the intricate solutions, a phenomenon comprising less convergence speed and low precision occurs. Consequently, grounded on the fundamental DA’s improvement, this work proposes the Improved DA (IDA) comprising the adaptive variable weight’s integration. The IDA’s steps as:

**Step 1** Initialize a \(n\) number of DFs’ population prevalent in the \(D\)-dimensional search space as:

\[
[\vec{d}] = (\vec{d}_1, \vec{d}_2, \ldots \vec{d}_n)
\]  

**Step 2** Examine every individual’s fitness values centred on its initial position, which is created arbitrarily betwixt the variables’ lower as well as upper bounds.

**Step 3** Enumerate the \(m\)th DF’s separation \(\vec{S}_i\) motion as:

\[
\vec{S}_i = -\sum_{j=1}^{n} \vec{d} - \vec{d}_j
\]

Here, \(\vec{d}\) signifies the current DF’s position; and \(\vec{d}_j\) is the jth adjacent DF’s position.

**Step 4** Enumerate the ith dragonfly (\(\vec{A}_i^{ln}\))’s alignment motion utilizing the Eq. (13)

\[
\vec{A}_i^{ln} = \frac{\sum_{j=1}^{n} \vec{V}_i}{n}
\]
Here, $\vec{V}$ signifies the $j$th adjacent DF’s velocity.

**Step 5:** Equate the $j$th DF ($h_i^{\vec{C}}$)’s cohesion as:

$$h_i^{\vec{C}} = -\frac{1}{n} \sum_{j=1}^{n} \vec{d}_j - \vec{a}$$  \hspace{1cm} (14)

Step 6: Enumerate the attraction ($fsR_i$) to a food resource and distraction ($eyD_i$) outwards to an enemy utilizing the Eqs. (15) and (16).

$$fsR_i = [\vec{d}]_{ps}^+ - [\vec{d}]$$  \hspace{1cm} (15)

$$eyD_i = [\vec{d}]_{ps}^+ + [\vec{d}]$$  \hspace{1cm} (16)

Here, $[\vec{d}]_{ps}^+$ signifies the food resource’s position; $[\vec{d}]_{ps}^-$ implies the enemy’s position.

**Step 7** Update the DFs’ position in the search space and then simulate their motions, by pondering ‘2’ vectors: step $\Delta[\vec{d}]_{vec}$ & position $\vec{d}vec$. The $\Delta[\vec{d}]_{vec}$, also pondered as speed, signifies the DF motions’ direction (Eq. 17). Past the computing of step vector, the $\vec{d}vec$ is updated (Eq. (18)):

$$\Delta d_{i+1} = (s'\tilde{S}_i + a'\tilde{A}_i + e_i^{hs} \vec{C} + r^{fs}R_i + e^{ey}D_i) + \omega w_i [\vec{d}]_{vec}^t$$  \hspace{1cm} (17)

$$[\vec{d}vec]^t = [\vec{d}vec]^t + (\Delta[\vec{d}]_{vec})^t$$  \hspace{1cm} (18)

Here, the values of $s'$, $a'$, $e'$, $r'$, and $e'$ signifies the coefficients of separation, alignment, cohesion, food factor, and also the enemy factor, $\omega$ and $dt$ implies the inertia weight, and iteration number. Over-large or else over-small inertia weight can affect the parameters’ estimation speed as well as its precision. The bigger adaptive variable weight utilized in the population evolution’s earlier period increments the particle’s movement speed and the global search capability strong. The smaller one utilized in the evolution’s later period decrements the particle’s movement-speed and also concentrates on the local search aimed at incrementing the optimal particle’s precision. So, this work utilizes the inertia weight non-linear decrementing stratagem for attaining the non-linear decrement with the number of iterations’ increment, which is,

$$w_i = w_{max} \left( \frac{T - t}{T - 1} \right)^\varepsilon + w_{min}$$  \hspace{1cm} (19)

Here $w_{max}$ signifies the inertia weight’s maximal value; $w_{min}$ implies the inertia weight’s minimum value; $t$ implies the prevalent number of iterations; $T$ symbolized the maximal number of iterations; $\varepsilon$ is the constant which is $\geq 0$. The coefficient above and the factors mentioned aids to perform the exploitative and explorative behaviours at optimization.
4 Result and Discussion

Here, a new BC aided IDA-DNN is put forward aimed at detecting the COVID-19 recovered patients’ various diseases. The proposed IDA-DNN design is employed in MATLAB’s operating platform. Entirely, 4 diverse diseases of COVID-19 patients are detected, like kidney, heart, liver, and lung. To find every disease, ‘4’ diverse data sets are utilized. Here, the IDA-DNN is analogized with the prevalent methods concerning the performance measures, like Sensitivity, Specificity, False Discovery Rate (FDR), Accuracy, Recall, Precision, F-measure, the False Negative Rate (FNR), and False Prediction Rate (FPR) aimed at 4 diverse data-sets. The prevalent and proposed protocol’s examination aimed at every disease is:

4.1 Performance Analysis of IDA-DNN for Liver Disease

The proposed IDA-DNN algorithm’s examination utilized the graph aimed at understanding good outcomes for analogizing with an existent algorithm, like Support Vectors Machine (SVM), Decision Tree, K- Nearest Neighbour (KNN), along with Naive Bayes (NB). The dataset is gathered as of the Egyptian Liver Research Institutes and also the Mansoura Central Hospital, Dakahlia Governorate, Egypt. Gathered 5000 patient’s data, wherein the patient’s age prevalent in the dataset ranges as of 4 to 90 years. Figure 3 exhibits that a dataset is created with ‘23’ features, which involves the 5000 patients’ records, wherein 3295 patients are male and the remaining are female. The outcomes are utilized to understand good performance. Diverse performance metrics are examined. Hence, here the proposed system’s performance is analogized with the existent methods. Diverse performance metrics are examined.

Figure 4a exhibits the IDA-DNN’s efficient outcomes. The proposed system’s sensitivity, specificity, as well as accuracy is greater analogized to other methods. The existent NB, Decision Tree, KNN, and SVM techniques’ accuracy is 33%, 41%, 51%, and 77%, but the IDA-DNN accuracy is 95%. The IDA-DNN’s precision is 82% that is greatest than the other techniques. Likewise, the IDA-DNN comprises an efficient recall (89%). Figure 4b exhibits the proposed method’s efficient performance. The IDN-DNN’s sensitivity, specificity, as well as F-measure are 98%, 90%, and 90%. Analogized with the other methods, the results showcase the proposed method’s efficient performance. Figure 4c elucidates the proposed method’s superior performance. The classification error detection rate is examined. The IDN-DNN’s FPR, FNR, and FDR are 0.0298, 0.0387, and 0.0021. The result exhibits less error detection rate aimed at the proposed protocol.

4.2 Performance Analysis of IDA-DNN for Lung Disease

The IDA-DNN’s performance is analogized with the existent methods utilizing Table 3. Diverse performance metrics are employed to get the proposed technique’s performance. A total of 300 datasets aimed at the diseases emphysema, bronchitis, pleural effusion, and also normal lung are employed aimed at training along with testing. The IDA-DNN and prevalent Naive Bayes, J48, KNN, and Multi-layer Perceptrons Neural Network (MLP-NN) results are examined employing diverse performance metrics.

Table 3 exhibits the proposed method’s efficient classification performance. The proposed IDN-DNN’s accuracy, precision, and recall are 92%, 86%, and 90%. These performance metrics are the greatest outcomes analogized to existent techniques. The sensitivity,
specificity, and F-measure values of the proposed system are 90%, 92%, and 90%. Whilst analogized to the prevalent Naive Bayes (NB), J48, KNN, and MLP-NN, the metrics’

Fig. 4 Performance analysis of techniques for liver disease
values are comparatively less. Likewise, the proposed IDN-DNN’s FPR, FNR, and FDR are 0.0198, 0.0287, and 0.0121. Consequently, the proposed method comprises less FDR whilst analogized to other methods.

4.3 Performance Analysis of IDA-DNN for Heart Disease

The adopted IDA-DNN’s performance evaluation aimed at the heart disease prediction is offered by Fig. 4 aimed at various learning percentages. As of the evaluation, efficient performance is attained by the proffered technique aimed at every measure. The dataset is downloaded as of the “http://archive.ics.uci.edu/ml/datasets/statlog+(heart)”. The offered dataset’s features are Multivariate in nature; the number of Instances prevalent is 369. The features’ Characteristics are categories and real. The number of features existent is 14 that involved age, sex, chest pain type (4 values), serum cholesterol in mg/dl, resting blood pressure, fasting blood sugar > 120 mg/dl, resting electrocardiographic outcomes. Figure 5 exhibits performance metrics are examined.

Figure 5a exhibits that the proposed IDA-DNN’s efficient performance analogized to prevalent techniques like Deep Belief Network (DBN), CNN, KNN, and Deep CNN (DCNN). The existent techniques classified accuracy is DBN (63%), KNN (78%), CNN (70%), and DCNN (87%), but the IDA-DNN (90%) possesses the greatest accuracy. Likewise, the IDA-DNN comprises the greatest precision and effectual recall. Figure 5b exhibits that the IDA-DNN encompasses the greatest sensitivity, specificity, and F-measure (90%, 91%, and 90%). Figure 5c depicts that the proposed IDA-DNN possess much low FDR whilst analogized to the existent techniques.

4.4 Performance Analysis of IDA-DNN for Kidney Disease

This evaluation is executed utilizing the proposed IDA-DNN. The employed techniques’ experiential analogy was executed grounded on the performance measures mentioned above. The dataset utilized in the examination comprises 461 CKD Indian patients and encompasses 35 variables (21 numerical, 14 categorical). The outcomes elucidate the proposed IDA-DNN’s efficient performance. Table 4 exhibits the proposed technique’s analogized analysis.

Table 4 reveals the IDA-DNN effectual performance along with the prevalent techniques, like SVM, Radial Basis Function (RBF), multilayer perceptron (MLP), and also

| Classifiers | Performance Metrics (%) | Accuracy | Precision | Recall | Sensitivity | Specificity | F-Measure | FPR | FNR | FDR |
|-------------|--------------------------|----------|-----------|--------|-------------|------------|-----------|-----|-----|-----|
| NB          |                          | 0.5309   | 0.4502    | 0.5802 | 0.5178      | 0.5462     | 0.5462    | 0.3536 | 0.2106 | 0.4457 |
| J48         |                          | 0.6124   | 0.5015    | 0.6997 | 0.6809      | 0.7018     | 0.6506    | 0.2698 | 0.1734 | 0.5638 |
| KNN         |                          | 0.7109   | 0.6978    | 0.7561 | 0.7506      | 0.8625     | 0.7419    | 0.1076 | 0.1524 | 0.4309 |
| MLP-NN      |                          | 0.8781   | 0.7085    | 0.8724 | 0.8909      | 0.8938     | 0.8103    | 0.0865 | 0.0908 | 0.2987 |
| proposed IDA-DNN |                  | 0.9029   | 0.8605    | 0.9035 | 0.9075      | 0.92561    | 0.9012    | 0.0198 | 0.0287 | 0.0121 |
Fig. 5 Performance analysis of techniques for heart disease
Probabilistic Neural Network (PNN). A feedforward neural network called a multilayer perceptron (MLP) creates a set of outcomes from a collection of sources. Several levels of input nodes are interconnected as a graph structure between both the input and output layers of an MLP. Back propagation is used by MLP to train the neural network. The IDN-DNN’s accuracy, precision, and recall are 90%, 89%, and 90%, but the prevalent methods possess lesser performance. Likewise, the IDA-DNN possesses the maximum F-measure, specificity, and also sensitivity values. The categorization error detection rate is much lesser analogized to other prevalent methods.

5 Conclusion

In this work, a BC aided IDA-DNN is proffered aimed at detecting the COVID-19 patients’ diverse diseases past a recovery period. Centred on the patients’ post symptoms, the disease kind is organized, and training is done aimed at disease prediction. For offering the privacy-preserving patient data, the BC concept is implemented that utilizes a trusted authority certificated to verify the patients and doctors; TAC offers the keys to both doctor and patient aimed at the data access. Next, the IDA-DNN’s training is proffered for finding if the patient is affected due to some serious disease (lung, liver, kidney, and heart) or not. The proposed IDA-DNN’s outcomes are analogized with the existent techniques aimed at ‘4’ diverse data-sets. The proposed IDA-DNN obtains the greatest values of sensitivity, specificity, precision, recall, f-measure, and accuracy analogized to the existent classifiers, which exhibits how effectively the IDA-DNN identifies the COVID-19 patients’ diseases. Moreover, the technique attains the least error metric values of FPR, FDR, and FNR, which exhibits that the IDA-DNN provides the least error whilst the data inputted is categorized. The IDN-DNN’s accuracy, precision, and recall are 90%, 89%, and 90%, but the prevalent methods possess lesser performance. The method is prolonged in the upcoming future by proffered a new technique to detect the paces of the COVID-19 patients’ various diseases utilizing the prevention technique.

| Classifiers | Performance metrics (%) | Accuracy | Precision | Recall | Sensitivity | Specificity | F-Measure | FPR | FNR | FDR |
|-------------|--------------------------|----------|-----------|--------|-------------|------------|-----------|-----|-----|-----|
| MLP         | 0.6309                   | 0.5502   | 0.6802    | 0.5178 | 0.5187      | 0.6562     | 0.3536    | 0.2106| 0.4457 |
| RBF         | 0.7024                   | 0.6015   | 0.7997    | 0.6809 | 0.6218      | 0.7506     | 0.2698    | 0.1734| 0.5638 |
| SVM         | 0.8009                   | 0.7978   | 0.8061    | 0.7606 | 0.7625      | 0.8419     | 0.1076    | 0.1524| 0.4309 |
| PNN         | 0.8981                   | 0.8085   | 0.8924    | 0.8169 | 0.8238      | 0.8813     | 0.0865    | 0.0908| 0.2987 |
| proposed IDA-DNN | 0.9019 | 0.8905   | 0.9035    | 0.9185 | 0.9261      | 0.9116     | 0.0198    | 0.0287| 0.0021 |
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