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A novel algorithm for detection of COVID-19 by analysis of chest CT images using Hopfield neural network

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ABSTRACT

Background: Widely spread of the COVID-19 virus has put the whole world in jeopardy. At this moment, using new techniques to detect and treat this novel disease is of significance or maybe the first priority of many scientists and researchers throughout the world.

Purpose: To present a new algorithm for detecting the novel coronavirus 2019 using chest CT images with high accuracy.

Materials and methods: In this study, we looked at the newly-presented data and detection methods of this disease using chest CT; then, a new neural network algorithm was presented to recognize the COVID-19 symptoms. A mathematical model is used to enhance the accuracy of masking, and a high accuracy Hopfield Neural Network (HNN) is used for finding symptoms. A dataset of CT scans, including 12 pattern images, was trained by this neural network, and 295CT images from three different datasets were tested via the model.

Results: The sensitivity and specificity of the model for detecting COVID-19 in test data were 97.4% (149 of 153) and 98.6% (140 of 142) respectively. Also, the sensitivity and specificity of the model for detecting CAP (community-acquired pneumonia) in test data were 97.3% (106 of 109) and 99.5% (185 of 186) respectively, and, the sensitivity and specificity of the model for detecting non-pneumonia patients were 100% (33 of 33) and 98.5% (258 of 262) respectively.

Conclusion: This new algorithm can potentially help detect the novel Coronavirus patients using CT images.

1. Introduction

The outbreak of the novel Coronavirus has endangered global health by spreading through many countries (Organization; Velavan and Meyer, 2020). Research has shown that NCP (novel coronavirus pneumonia) patients with a background of diseases like hypertension, diabetes and coronary heart disease are at high risk of mortality (Fang, Karakiulakis & Roth, 2020; Zhou et al., 2020). Also, it is imperative to recognize the disease and set pregnancy-specific care for pregnant women owing to diverse symptoms of Covid-19 pneumonia (Chen et al., 2020; Rasmussen et al., 2020). There is limited knowledge about this virus, so scientists believe that the best method to control this new pandemic is preventing the spread of disease from one person to another (Lai et al., 2020). So, early screening and recognition of this disease can be effective in the reduction of NCP mortality rate; in addition, being aware of symptoms would be of benefit to tackling this global threat (Sohrabi et al., 2020; Sun et al., 2020).

Digital technology can be productive to find and boost public-health strategies. The application of this technology can help us to cope with new viruses like COVID-19 or other probable ones in the future (Ting et al., 2020). The role of CT imaging has been taken into consideration for recognizing patients and the severity of disease (Ng et al., 2020). The feasibility of a computer-based tool for recognition of novel Coronavirus infection along with the severity of the disease has been proved, compared to the declared results of radiologists. In a survey, 44 computed tomography CT images were applyed which all of them were confirmed Covid-19 cases (Shen et al., 2020).

The significance of using CT scans have been studied by different

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A new survey has shown that chest CT is more likely to give us more accurate results of diagnosis of COVID-19 rather than RT-PCR. In this study, 51 patients were checked by both methods, CT scans and RT-PCR, for diagnosis of viral disease (Fang et al., 2020). Chest CT image can distinguish the Coronavirus Disease-19 during the infection. 121 symptomatic patients were checked in order to find the relationship between CT images and duration of infection (Bernheim et al., 2020). Testing chest CT and RT-PCR methods on 1014 cases to diagnose viral disease COVID-19 showed that the high accuracy of CT scans. Although reverse-transcription polymerase chain reaction (RT-PCR) assay has been considered as the main way of diagnosis, chest CT should be taken into account to find infection caused by this novel virus (Ai et al., 2020).

An efficacious artificial intelligence algorithm needs valid data about signs and symptoms of a disease due to resulting efficient as well as advantageous information regarding the recognition of COVID-19 and its severity. By analyzing 149 patients’ symptoms, with positive RT-PCR, clinical characteristics and image manifestations of COVID-19 were reported. Fever, cough, expectoration, decreased oxygen saturation, leukopenia, lymphopenia, and elevated C-reactive protein have been observed; In addition, ground glass opacity and consolidation have been found in CT scans where the peripheral lung was mostly involved (Yang et al., 2020). Another analysis of radiological findings has been done for 81 patients in Wuhan; patients were COVID-19 pneumonia confirmed using next-generation sequencing or RT-PCR. Different observations of CT images included ground-glass opacity, consolidation pattern and crazy-paving pattern; these patterns were either separated or mixed in lungs’ lobes (Shi et al., 2020).

A study of clinical characteristics of the COVID-19 cases, six patients between 27 and 63, has been carried out in order to diagnose the disease with a high level of accuracy. Patchy-like pure ground glass opacity (GGO), the crazy paving sign, and mixed GGO along with consolidation were found in the subpleural regions and the central areas of lobes. The study resulted that COVID-19 has a diversity of appearances (Zhu et al., 2020). Another study of the severity of lung involvement in COVID-19 pneumonia has been done using CT images in a 26-day period. This study gave rise to defining 4 stages of lung CT, including ground glass opacities (GGO), increased crazy-paving pattern, consolidation and gradual resolution of consolidation without crazy-paving pattern (Pan et al., 2020).

The severity of COVID-19 is divided into three stages: mild, moderate, and severe. Patients with mild viral disease may show only lymphopenia and neutrophilia in their CBC test (complete blood count). Patients with a moderate level of Covid-19 may reveal fever, cough, hypoxia and ground glass opacity (by screening CT scan). Finally, in patients with severe viral disease, elevated systemic inflammation may be revealed; moreover, shock, vasoplegia, respiratory failure, and cardiopulmonary collapse are recognizable in this stage (Rao & Vazquez, 2020).

Ref. (Kelez, Kelez and Yavuz 2011), using expert systems based on neuro-fuzzy rules, diagnosed breast cancer. They developed an expert system called EX-DBC (Expert System for Diagnosis of Breast Cancer) which is used as a powerful diagnostic tool with 97% specificity, 76% sensitivity, 96% positive and 81% negative predictive values for diagnosing breast cancer. Ref. (Chen et al., 2012) compared the diagnostic performances of Artificial Neural Networks (ANNs) and multivariable Logistic Regression (LR) analyses for contradiestinction between malignant and benign lung nodules on computed tomography (CT) scans.

The capabilities of neural networks are known by many researchers. Ref. (Khatami et al., 2020) proposed a new regularization approach for the convolutional neural network. They represented experimental results on a number of medical benchmark data sets for proving that this approach provides a better prediction model. Ref. (Jolai and Ghanbari 2010) presented a paper for solving the travelling salesman problem (TSP) with an improved ANN approach. Using HNN and Data Transmission Techniques (DIT) together, they improved the accuracy of the results.

Artificial intelligence techniques are used in several medical problems. For brain tumour grade identification, Ref. (Subashini et al., 2016) developed a non-invasive method. They used magnetic resonant images consisting of training data (164 images) and test data (36 images). The process involves preprocessing, image segmentation, tumour isolation, feature extraction, feature selection, and classification. A study has been established an early screening model to distinguish Influenza-A viral pneumonia and normal cases from COVID-19 by Xu et al. (2020) through pulmonary CT images using deep learning techniques. In this paper, CT images were obtained from three hospitals in Zhejiang province, China. Meanwhile, The Deep Learning models, which have been established in this paper, were influential with high accuracy results.

A neuro-heuristic approach –proposed by Ref. (Ke et al., 2019) for recognition of lung disease from X-ray images- provides decision support for the doctor to help to consult each case faster and more precisely. For detecting lung tissues in X-ray images, they used image descriptors based on the spatial distribution of Hue, saturation and brightness values in X-ray images and a neural network co-working with heuristic algorithms. A comparison of Deep Conventional Neural Network (DCNN) architectures presented by Asnaoui, Chawki and Idiri (2020) using chest X-ray and CT images for automatic classification of pneumonia patients. The architectures of Deep Learning includes DeseNet201, MobileNet-V2, Resnet50, VGG16, VGG19, Inception_ResNet_V2, Inception_V3, and Xception; Consequently, Resnet50, MobileNet_V2 and Inception_Resnet_V2 have given rise to more accuracy (96%) than others.

Ref. (Gruden et al., 2020) suggested an algorithmic approach to the rendition of thin-section CT images of the chest with a focus on lung parenchymal evaluation. Discussing the optimal scan technique, they then presented a systematic approach to thoracic image interpretation based on initial uninterrupted scrolling through the thin section images. Ref. (Pereira et al., 2020) presented a classification schema considering a multi-class classification, and hierarchical classification. Because of being cheaper, faster and more widespread of X-ray scan, they chose this method among two standard image diagnosis tests for pneumonia, chest X-ray (CXR) and computed tomography (CT) scan.

Apostolopoulos and Mpesiana (2020) proposed a model for the detection of Coronavirus using a conventional neural network. They claimed the procedure called Transfer Learning (TL) has been adapted and using TL, the detection can be an achievable target. It uses X-ray images collected from two datasets. The collections of X-ray images include images with confirmed COVID-19 disease, common bacterial pneumonia, and normal condition. The accuracy, sensitivity, and specificity of the model are 96.78%, 98.66%, and 96.46%, respectively. Brunese et al. (2020) proposed a method for the detection of COVID-19 by chest X-ray images. The supervised machine learning technique has been utilized in this paper was effective in the discrimination between COVID-19 disease and other pulmonary diseases. Meanwhile, training and testing were two main phases in this method. Finally, the results indicated an average precision and recall equal to 0.96 in the differentiation between the COVID-19 and other pulmonary diseases.

Some studies were carried out in order to detect Covid-19 patients using image processing algorithms. A deep learning model was presented to detect Covid-19 using chest CT. A big dataset has been used to train a convolutional neural network. The model classifies a series of CT images to protect the infected chests by the novel Coronavirus; subsequently, his virus would be distinguished from other lung illnesses (Li et al., 2020). Also, other deep learning approaches were presented to detect novel Coronavirus by screening either CT or X-ray images. Different classification methods were used in these studies (Abbas, Abdelsamea & Gaber 2020; Butt et al., 2020; Chowdhury et al., 2020; Farid et al., 2020; Gozes et al., 2020; Loey, Smarandache and Khalifa 2020; Wang et al., 2020; Zhang et al., 2020; Zheng et al., 2020). The spread of the novel Coronavirus through the world has brought a large number of orders for medical masks. Chen et al. (2020) proposed an end-
to-end neural network model for the production of medical masks in which this model takes a sequence of producing as inputs and creates a schedule of tasks in a real-time manner.

Hopfield neural network is a large network with a graded response similar to a dynamic system with two or more stable points of equilibrium. Starting from any initial condition, the system eventually converges to one of its equilibrium points. Convergence to any point of equilibrium is a diagnosis made by the neural network and can actually be used as an approach to solving classification problems. HNN is one of the oldest types of neural networks that has a recursive structure, and in its structure, there is internal feedback. HNN can potentially be useful for image segmentation which shows remarkable results (Cheng, Lin & Mao, 1996).

In this paper, we presented a new algorithm to find COVID-19 symptoms using CT images. Ground glass opacity (GGO), the crazy paving sign, and consolidation have been considered as the main patterns of finding lesions in lung lobes. A Hopfield neural network is an efficient way to segment CT images; then, the algorithm would be able to detect lesions (Hopfield, 1984). Obtaining an appropriate mask, we used an operation research model in which this LP model is able to make a proper estimation of the thresholds of lung lobes (see Table 1).

2. Methodology

Due to the outbreak of the novel Coronavirus and the importance of diagnosis of this disease from other pneumonia-related illnesses, we presented a new method for detection of this disease’s symptoms using chest CT scans. This method can differentiate COVID-19, non-pneumonia, and other pneumonia types by distinguishing lessons caused by infections in chest lobes. After collecting 295 chest CT images from three different databases, we used them to test the proposed algorithm; the results were satisfying with high accuracy. The presented algorithm performs two steps to detect COVID-19: masking the lungs, and finding the symptoms. Three types of symptoms have been considered to distinguish NCP which are shown in Fig. 1.

Input CT images should be resized in order to construct matrices with the dimension of 512 × 512. In the first step, after filtering the CT image, a Hopfield neural network is run for different parts of cells in the big matrix. This HNN searches for lungs. Having found the lungs, they need to be masked. At this point, the specification of lungs’ edges may conceivably be difficult, especially in lobes owing to some consolidation areas next to the thresholds. So, the algorithm uses a mathematical model to estimate the edged. The following model is solved twice for each lung to find the outer and lower edges.

\[
\begin{align*}
\text{Max} & \sum_{i=0}^{8} x_i^2 a_i, \\
\text{subject to :} & \\
\sum_{i=0}^{8} x_i a_i \leq y_k \forall k \in K \\
a_k \in \mathbb{R}/n = 0, \ldots, 8
\end{align*}
\]

The purpose of the model is to find the best polynomial curve to fix the lower edge of the lungs; then, searching for coefficients of an optic function can be helpful for this purpose.

In this model, K is the set of cells in the lower edge of a lung in the double matrix; subsequently, x_0 and y_k are the row number and column number of k th cell respectively. The model maximizes the summation of output amounts of polynomial function for all x_k s (k ∈ K). Constraint (2) guarantees that output amount of polynomial for each x_k (k ∈ K) is less than or equal to y_k. Equation (3) is the definition of a_k which are the coefficients of polynomial function.

Also, it is possible to use this model for curve fitting the outer thresholds of lungs by rotating the matrix. Fig. 2 shows the lower and outer edges and final mask for a lung in a CT image.

In the next step, the algorithm searches for lesions in masked lungs using a Hopfield neural network. Ground Glass Opacity (GGO), the crazy paving sign, and consolidation are taken into account as main patterns for the identification of similar ones in the lungs. Running HNN needs to create vertical matrices which take values of 1 and −1. Then, it would be difficult to create the binary matrices of the main patterns and find patterns as similar as the main ones in the binary matrix of lungs. For this problem, we transformed the input matrices in the neural network. The dimension of main patterns’ matrices has been considered 20 × 20, and they need to be reshaped to 400 × 1 dimension matrices with cells of 1 and −1. For enhancing the accuracy of the searching algorithm, we change each 20 × 20 input matrix to an 800 × 1 matrix with cells of 1 and −1 by applying the following function.

\[
f(n) = \begin{cases}
-1M_p \left[ \frac{n + 1 - \left[ \frac{n - 1}{\lambda} \right] \times \lambda}{2} \right] + 1 < 0.25 \\
(1)0.25 \leq M_p \left[ \frac{n + 1 - \left[ \frac{n - 1}{\lambda} \right] \times \lambda}{2} \right] + 1 < 0.5 \\
(1)0.5 \leq M_p \left[ \frac{n + 1 - \left[ \frac{n - 1}{\lambda} \right] \times \lambda}{2} \right] + 1 < 0.75 \\
10.75 < M_p \left[ \frac{n + 1 - \left[ \frac{n - 1}{\lambda} \right] \times \lambda}{2} \right] + 1
\end{cases}
\]

This function outputs the value of n th cell of a vertical matrix -an appropriate input mask for HNN- which is reshaped of matrix M_p. In
fact, this function transforms a $20 \times 20$ matrix, with decimal values between 0 and 1, to an $800 \times 1$ matrix, with values of 1 and $\lambda$. $\lambda$ is twice as much as the number of the rows (or the columns) of the input matrix which is considered 40 in this algorithm. Furthermore, this method divides the grayscale spectrum from black to white into four spectrums. Fig. 3 illustrates the transformation of a cell to a pair of cells using the presented function.

This algorithm detects lesions based on the aforementioned main patterns. The flow chart of the algorithm is shown in Fig. 4. In each loop, the algorithm analyzes one of the CT images. After locating lungs using Hopfield neural network, they are masked with the help of the presented operational research model. In the following step, another Hopfield neural network is trained to find the symptoms through the lungs. In this step, the algorithm divides the CT image into $20 \times 20$ images; then, they are transformed to $800 \times 1$ matrices using the presented function. These changes are owing to easing the comparison between these pieces and the patterns. Finally, after analysis of all CT images, the patient will be classified into one of three groups of normal, COVID-19, and CAP (community-acquired pneumonia).

3. Experimental results

Using MATLAB software, the model has been performed for 295 chest CT images -black and white- with the resolution of $512 \times 512$ pixels from three different datasets (121 images from the first dataset (1st dataset), 105 images from the second dataset (2nd dataset), and 69 images from the third dataset (3rd dataset)). Three classes have been considered to differentiate the CT images: COVID-19, CAP, non-pneumonia. The model was trained by 12 pattern images with a resolution of $20 \times 20$ pixels, 11 lesion images and a slice of a healthy lung image. $\lambda$ has been assumed 40 in which this value depends on the size of pattern images, so this would be changed by altering the resolution of patterns. After running the algorithm, studying patients were classified into three classes. By the confirmed information regarding the patients,

\[
\begin{align*}
\text{If} & \quad M_p(i, j) < 0.25 \quad \rightarrow \quad M_p^1(k, 1) = -1 \land M_p^1(k + 1, 1) = -1 \\
\text{If} & \quad 0.25 \leq M_p(i, j) < 0.5 \quad \rightarrow \quad M_p^1(k, 1) = -1 \land M_p^1(k + 1, 1) = 1 \\
\text{If} & \quad 0.5 \leq M_p(i, j) < 0.75 \quad \rightarrow \quad M_p^1(k, 1) = 1 \land M_p^1(k + 1, 1) = -1 \\
\text{If} & \quad 0.75 < M_p(i, j) \quad \rightarrow \quad M_p(k, 1) = 1 \land M_p(k + 1, 1) = 1
\end{align*}
\]

Fig. 3. Transforming a decimal element from a matrix to two elements belonging to $\{ -1, 1 \}$ using presented function.
we compared clinical results with our model’s output. As it is shown in Table 2, the sensitivity of the algorithm for test data, for detection of COVID-19 patients, was approximately 97.4%, and the specificity was calculated around 98.6%; also, sensitivities and specificities have been calculated for CAP (community-acquired pneumonia), and non-pneumonia patients’ detection. In addition, Table 2 shows the sensitivities and specificities of three classes for three datasets separately.

Fig. 5 shows detected areas of infection in a chest CT image. What makes the algorithm capable of finding COVID-19 symptoms with high levels of accuracy is analyzing more slices of lungs images. We chose 10 pixels as the step of selecting the next slice. Running the algorithm at an appropriate period of time and enhancing the accuracy of detecting lesions, this value can potentially be suitable.

Miss-classification occurs when either some miss-classified labels of the rest of the classes are classified to a class (false positive labels), or some miss-classified labels of the class under observation are classified to other classes (false negative labels) (Loey, Smarandache & Khalifa, 2020). In this case study, three confirmed COVID-19 patients and a CAP have been classified to the non-pneumonia class; moreover, the algorithm classified two CAPs to the COVID-19 class, and one COVID-19 patient to the CAP class. These miss-classifications are due to some small lesions and similar symptoms. For instance, because of the proper response of the immune system to infection in a person’s body, the infected areas in the lungs are very small, so it would affect the accurate diagnosis of the disease.

Clearly, tested data has been classified with high accuracy; thus, the proposed algorithm acted efficiently in this case study.

4. Discussion

Disease detection methods have a significant as well as a momentous role to play in order to stop spreading and treat the patients. Subsequently, many medical scientists and researchers are seeking new techniques for more and more accurate and quick detection of diseases. In this paper, different detecting methods of the novel coronavirus 2019 were introduced. Analysis of chest images is more likely to detect this disease with high accuracy. In addition, various symptoms of COVID-19 were introduced, and proposed models and algorithms for the detection of COVID-19 using chest CT and X-ray images have been compared. In the proposed model, we consider the lesions and symptoms of the coronavirus 2019 to enhance the precision of patients detection. Different symptomatic patterns of COVID-19 and CAP have been taken into account to train the algorithm. In a case study with 295 test data, some miss-classifications occurred owing to small lesions and similar imaging symptoms caused by other kinds of viruses. Besides small infection areas, another limitation is the variety of respiratory-related illnesses with similarities in lung infections which may be confusing to diagnose for some special patients. These limitations gave rise to some minor errors, so the algorithm might probably make mistakes in similar

### Table 2
Comparing the output of the model using CT scans with the clinical diagnosis results.

| Dataset | Class       | Sensitivity % | Specificity % |
|---------|-------------|---------------|---------------|
| 1st dataset | Covid-19    | 95.4 (41 of 43) | 98.7 (77 of 78) |
|          | CAP         | 96.8 (60 of 62) | 98.3 (58 of 59) |
|          | Non-pneumonia | 100 (16 of 16) | 98.1 (103 of 105) |
| 2nd dataset | Covid-19    | 98.3 (59 of 60) | 97.8 (44 of 45) |
|          | CAP         | 96.9 (31 of 32) | 100 (73 of 73) |
|          | Non-pneumonia | 100 (13 of 13) | 98.9 (91 of 92) |
| 3rd dataset | Covid-19    | 98 (49 of 50) | 100 (19 of 19) |
|          | CAP         | 100 (15 of 15) | 100 (54 of 54) |
|          | Non-pneumonia | 100 (4 of 4) | 98.5 (64 of 65) |
| All      | Covid-19    | 97.4 (149 of 153) | 98.6 (140 of 142) |
|          | CAP         | 97.3 (106 of 109) | 99.5 (185 of 186) |
|          | Non-pneumonia | 100 (33 of 33) | 98.5 (258 of 262) |

Fig. 4. Flow chart of the presented algorithm for detection of COVID-19 using chest CT images.

Fig. 5. Diagnosed areas infected by Coronavirus in a CT image using proposed algorithm.
cases. Also, despite using a sufficient number of images for training and testing the proposed algorithm, big size dataset from a variety of countries can potentially give more accurate information and results. Eventually, the lack of enough information about COVID-19 makes it difficult to analyze the severity level of this disease. Apparently, accurate data for categorization of the severity of COVID-19 can be helpful to operate more efficiently and choose more appropriate treatments.

Furthermore, a Friedman test was performed in order to find differences in the performance of the algorithm using various training sets. The model has been run six times with six different training data (A, B, C, D, E and F). Also, we used all 295 test data as blocks for six performances. In this Friedman test, the null hypothesis is that there is no any significant difference between classifiers. The results are shown in Table 3. The table provides test statistic ($\chi^2$) value in 1.667, degree of freedom in 5, and the significance level in 0.893; thus, null-hypothesis is correct (Demser, 2006).

The mean ranks, shown in Table 4, illustrate no critical difference between these results. Different training sets have been used to run the algorithm on the test data, and the closeness of mean ranks indicates that the algorithm with different training sets acted similarly. Although it is significant to use appropriate data to train the Hopfield neural network, using various data made no different results.

5. Conclusion

The role of artificial intelligence is undeniable in our lives along with in the future of humans. With new inventions and developments, we are able to use machines to ease and accelerate the activities and calculations which may be, in some cases, crucial. Clearly, using machine learning algorithms have been common in medical fields for the early detection of serious illnesses. In this paper, we reviewed various studies done as to the novel coronavirus symptoms and detection algorithms; then, a new algorithm was presented in order to detect the novel Coronavirus patients using chest CT scans. In this algorithm, Hopfield neural network is used twice, first, for masking CT images to distinguish the lungs, second, for finding infection in the lungs. In addition, the algorithm applies an operational research model as well as a matrix transformation function to enhance the accuracy of masking and detecting the lesions respectively. The algorithm was trained by five lung-shaped images to locate the lungs, it was also trained by eleven lesion patterns to detect the disease. Then, 295 patients’ CT images were tested by the algorithm. The sensitivity, specificity, and precision of this algorithm for COVID-19 patients detection were 97.4%, 98.6%, and 998.7% respectively. Also, a sensitivity of 97.3% and a specificity of 99.5% resulted for CAP, and the sensitivity and specificity for the non-pneumonia class resulted in 100% and 98.5% respectively. Seven patients were miss-classified due to some small lesions or similar symptoms. Carrying out a non-parametric ranking based Friedman test shows the proposed method performed accurately with different training sets. Using this method can potentially be beneficial to early diagnosis of this new pandemic; subsequently, this can be helpful to take care of patients appropriately which is more likely to reduce the Coronavirus mortality rate. Furthermore, early diagnosis and quarantining suspicious patients may conceivably cut down the contagion speed.

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CRediT authorship contribution statement

Saeed Sani: Conceptualization, Methodology, Project administration, Writing – original draft, Software, Visualization, Formal analysis.
Hossein Ebrahimzadeh Shermeh: Conceptualization, Software, Validation, Resources, Writing – review & editing, Visualization.

| Method (Classifier trained by | Mean rank |
|-----------------------------|-----------|
| A                           | 3.51      |
| B                           | 3.49      |
| C                           | 3.51      |
| D                           | 3.48      |
| E                           | 3.51      |
| F                           | 3.51      |

Table 4

Mean ranks of the method using different training sets.

Table 3

Friedman test results.

| Method | N   | Chi-Square | df | Asymp. Sig. |
|--------|-----|------------|----|-------------|
|        | 295 | 1.6667     | 5  | 0.893       |

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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| F                           | 3.51      |

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5. Conclusion

The role of artificial intelligence is undeniable in our lives along with in the future of humans. With new inventions and developments, we are able to use machines to ease and accelerate the activities and calculations which may be, in some cases, crucial. Clearly, using machine learning algorithms have been common in medical fields for the early detection of serious illnesses. In this paper, we reviewed various studies done as to the novel coronavirus symptoms and detection algorithms; then, a new algorithm was presented in order to detect the novel Coronavirus patients using chest CT scans. In this algorithm, Hopfield neural network is used twice, first, for masking CT images to distinguish the lungs, second, for finding infection in the lungs. In addition, the algorithm applies an operational research model as well as a matrix transformation function to enhance the accuracy of masking and detecting the lesions respectively. The algorithm was trained by five lung-shaped images to locate the lungs, it was also trained by eleven lesion patterns to detect the disease. Then, 295 patients’ CT images were tested by the algorithm. The sensitivity, specificity, and precision of this algorithm for COVID-19 patients detection were 97.4%, 98.6%, and 998.7% respectively. Also, a sensitivity of 97.3% and a specificity of 99.5% resulted for CAP, and the sensitivity and specificity for the non-pneumonia class resulted in 100% and 98.5% respectively. Seven patients were miss-classified due to some small lesions or similar symptoms. Carrying out a non-parametric ranking based Friedman test shows the proposed method performed accurately with different training sets. Using this method can potentially be beneficial to early diagnosis of this new pandemic; subsequently, this can be helpful to take care of patients appropriately which is more likely to reduce the Coronavirus mortality rate. Furthermore, early diagnosis and quarantining suspicious patients may conceivably cut down the contagion speed.

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Saeed Sani: Conceptualization, Methodology, Project administration, Writing – original draft, Software, Visualization, Formal analysis.
Hossein Ebrahimzadeh Shermeh: Conceptualization, Software, Validation, Resources, Writing – review & editing, Visualization.
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