Patient Classification Using the Hybrid AHP-CNN Approach

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Abstract. Covid19 is a horrible disease, which upset our life everywhere. The main complexity of this disease lies in its rapid evolution and through people’s contact and gaps in our understanding. Moreover, it represents critical cases when the immune system has not presented any symptoms. Hence, the design of an effective classifier is necessary. This paper aims to hybrid the multi-criteria Analytic Hierarchy Process (AHP) tool and the process of the convolutional neural network (CNN), for making the classification of a category of patients. Our novel method is divided into two main phases: the first one focuses on the generation of the priorities of the essential criteria using the AHP model, while the second phase aims to classify the patients using the neural network classifier. In the present study, we considered three important criteria: fever, patient localization, and the age of the patient. From the obtained results, the proposed model has proved its efficiency even if we consider different cases.

Keywords: Covid19 · Healthcare · AHP · Machine learning · CNN

1 Introduction

By the end of 2019, humanity was on a date with a horrible health crisis that started at a wildlife market in Wuhan and then spread in the whole world quickly. Novel coronavirus (COVID-19) pandemic [1], instigated by a novel coronavirus [2], has upset the world meaningfully, not only the healthcare system but as well economics, transportation, education, etc. Diseased COVID-19 people normally experience respiratory infection and can recuperate with real and appropriate treatment methods [3]. What makes COVID-19 much more unsafe and easily spread than other Coronavirus families is that the COVID-19 coronavirus has become extremely efficient in human-to-human transmissions [4]. Until now as the writing of this paper, the COVID-19 virus has spread quickly in 215 countries, causing diseased more 3 million people, and 207 thousand dead cases. Since, several governments, academia, and industries. Also, the global effort to develop an efficacious vaccine and medical handling for the COVID-19 coronavirus, computer science, and technology researchers makes initial efforts for
the fight versus COVID-19. Meanwhile, technology leaders, including Alibaba [5], Huawei [6], and others, have accelerated their company’s health initiatives. These young tech companies are working closely with caregivers, academics, and institutions around the world to make the best use of technology, while the virus continues to spread to many other countries. Interested by the enormous success of Artificial intelligence AI and big data in several areas, we present many works done of new technology, solutions, and approaches based on AI, and big data are used to fighting and attacking for the COVID-19 coronavirus illness [7]. We find AI for identifying, monitoring, and predicting houses, by this proposal they will be able to follow the virus, the better we will be able to fight it. By making the analysis of different sources such as newsletters, and social media, AI can learn to detect an epidemic. Also, AI company Infer vision has launched an AI-based solution that helps front-line caregivers effectively detect and monitor the disease. The medical imaging services of health facilities are subject to a heavy workload increased by the virus. Robots sterilize [8], a book of food and supplies, among others, and are therefore deployed to perform many tasks: cleaning, sterilization, delivery of food, and medicine to reduce contact between humans. This paper is organized as follows: Sect. 2 presents a recent review of the studies directed in the context of the classification of data using the neural network process. Section 3 describes the proposed methodology and includes a brief details about the combined methods. Section 4 presents the evaluation of the proposed work. Section 5 concludes the paper.

2 Related Works

Several studies have been proposed for the classification of data using the neural network. In this section, we present some recent works based on the CNN process. A global review of the different works proposed for COVID’19 [9], where the different methodologies are explained. Deep learning has been used as a powerful tool for achieving healthcare goals. In [10], authors have proposed the use of deep learning to detect the patients infected by the Influenza from those infected with the COVID’19. Similarly, in the work proposed in [11], authors have exploited the process of a deep CNN to identify the patients infected with the coronavirus. This study focuses on analyzing the chest radiography. Similarly, authors in [12] proposed the classification of the patients infected to COVID-19 by the use of the DenseNet201 deep transfer learning (DTL). In this study, a pre-trained is exploited to categorize the patients in those infected and not infected. CNN has been firstly proposed for making the classification of images. The different symptoms of COVID-19 are discussed in several studies such as the review presented by authors in [13]. Several works have been studied the feature extraction of images using a lot of techniques like the color information [14] or the meta-heuristic tools. However, the work proposed in [15] has argued that CNN can be applied to classify the generic data. This is realized by the conversion of each instance into the most suitable format. To achieve this goal, authors have proposed the conversion of a generic dataset to a matrix that represents an image
format. The work is compared to 22 benchmarks and it has represented a significant accuracy. In this global pandemic situation, the integration of technology, artificial intelligence, and data science has become a promising solution to assist societies to overcome this horrible situation. In the previously reviewed works, it is clear that the process of CNN has assisted the healthcare systems. To the best of our knowledge, our study based on the hybrid model proposed for the classification of patients has not previously been presented. The combination of the AHP model for generating the weights of criteria, with the CNN model represents a strong tool to classify the patients infected with COVID’19.

3 Proposed Work

3.1 Deep Learning

Deep learning represents machine learning that has the capacity to learn from the available data and achieve several tasks. In machine learning, we distinguish three major categories as shown in Fig. 1: [16]

- Supervised Learning
- Unsupervised learning
- Reinforcement learning

The first category focuses basically on the classification and regression tasks. Its learning is based on labeled data, while the unsupervised kind didn’t necessitate any supervision. This model operates itself for discovering the information. Table 1 presents a comparative study between these two techniques [17].

3.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are mainly based on a set of inputs and a unique output. This output is expressed by a mathematical function, named as the activation function as shown in Fig. 2. The output is a linear or non-linear function, which is responsible to search the activation of neurons using a threshold [18].

\[ Y = f\left(\sum_{i=1}^{D} w_i s_i + w_0\right) \]  

(1)

Neural networks [19] income inspiration from the learning procedure occurring in human brains. It is a multi-layer system, where each layer focuses on unique or a set of neurons. Figure 3 depicts this architecture, where the neurons are represented by circles. This architectural system is basically composed of three layers: the first one represents the inputs of the system, the second one plays a role of intermediate between the first and the last layer. The third layer depends totally or partially on the previous layers and it is responsible for making the classification task. The CNN represents a mathematical tool that is mainly
Fig. 1. The machine learning categories

composed of three kinds of layers: convolution, pooling, and fully connected layers. The first and the second layers are responsible for making the extraction, while the third layer represents a connected layer. The third layer consists of mapping the output of the previous layer as a classification. It is the key layer for CNN that is purely based on mathematical operations such as the convolution operation. They contain an artificial network of functions, named parameters, which permits the computer to learn and to fine-tune itself, by analyzing new data. Each parameter, known as neuron represents a function that receives one or different inputs and products an output. The produced outputs are used as inputs of the next layer of neurons. The process continues similarly to produce a final output, which represents the model result. The task of classifying data is to choose class association $y$ of an unidentified data item $x$ based on a data set $D = (x_1, y_1), \ldots , (x_n, y_n)$ of data items $x_i$ with known class associations $y_i$. Figure 4 shows the neural network process. The CNN is typically composed of three layers: convolution layer, pooling layer, and the fully connected layer.

- **Convolution layer:**
  It represents the first layer of the CNN’s architecture that is responsible for making extraction of features from an image. It can be mathematically defined as a function with two main parameters: the image matrix and a filter.

- **Pooling layer:**
  It plays the role of an intermediate layer, which is based on reducing the number of the image’s parameters when they are too large. Spatial pooling consists of reducing the maps’ dimensionality taking into account the importance of information. We distinguish between different kinds of spatial pooling:
  - Max pooling
  - Average pooling
  - Sum pooling
- Fully connected layer:
  Called also the FC layer, its first task is converting the input matrix in a vector and then creating the model using the combination of features. The major task is the classification of the outputs by the use of an activation function as the sigmoid or softmax functions. The accuracy measure is exploited to validate the classification using CNN. It is calculated by dividing the number of the correct classifications by the total number of items as expressed the following equation:

\[
A_c = \frac{T_{pos} + T_{neg}}{T_{pos} + T_{neg} + F_P + F_N}
\]  

Where:

\(T_{pos}\): the patients that are classified into the positive category [20].

\(T_{neg}\): the patients that are classified into the negative category.

\(F_P\): the patients that are incorrectly classified into the positive category.

\(F_N\): the patients that are incorrectly classified into the negative category.

It is required to calculate the F-measure (\(F_m\)) in some cases, where the evaluated dataset has imbalance classes. This measure is calculated as follows [21]:

\[
F_m = \frac{2 \times P_r \times R_c}{P_r + R_c}
\]
where: $P_r$ represents the precision of the classifier. A low value means that the classifier has a significant number of FP. The precision measure is mathematically formulated as:

$$P_r = \frac{T_{pos}}{T_{pos} + F_P}$$  \hspace{1cm} (4)

Another measure can be calculated for proving the completeness of the classifier. It is known as Recall ($R_c$). Its mathematical expression is as follows:

$$R_c = \frac{T_{pos}}{T_{pos} + F_N}$$  \hspace{1cm} (5)

On the other hand, it is possible to evaluate the patients, which are categorized as those that are not infected by the COVID19. Its mathematical formulation is as follows:

$$P_r = \frac{T_{neg}}{T_{neg} + F_P}$$  \hspace{1cm} (6)
### Table 1. Comparison of the supervised learning via the unsupervised learning.

| Parameters          | Supervised learning                                      | Unsupervised learning                                   |
|---------------------|----------------------------------------------------------|----------------------------------------------------------|
| Process             | Necessite a number of inputs and outputs                  | Necessite a given number of inputs                       |
| Input data          | Uses a labeled data                                      | Uses unlabeled data                                      |
| Algorithms          | Support vector machine (SVM)                             | Cluster algorithms                                       |
|                     | Neural networks                                          | K-means                                                  |
|                     | Classification trees                                     | Hierarchical clustering                                  |
| Complexity          | Simple                                                   | Computationally complex                                  |
| Use of data         | Based on training data technique                         | Requires only the inputs                                 |
| Accuracy of results | High accuracy                                            | Low accuracy                                             |
| Real-time learning  | Offline process                                          | Real time process                                        |
| Number of classes   | Known                                                   | Unknown                                                  |
| Drawbacks           | Big data represents a critical challenge                  | Data sorting does not offer precise information and outputs are unknown |

### 3.3 The Multi-criteria AHP Method

The AHP tool is one of the multi-criteria methods \[22,23\] that are exploited for ranking the alternatives of decision problems. Moreover, it is known as a strong tool for calculating the weights of criteria. In this goal, we have proposed the use of this tool for the calculation of the importance value of the criteria weights. AHP is mainly composed of these steps:

1. **Step1:** Making the decomposition of the decision problem into essential criteria.
2. **Step2:** Attribute the different values of the importance of each criterion using the Saaty scale as shown in Table 2.
3. **Step3:** Determine the relative importance of factors by the calculation of the eigenvectors corresponding to the maximal eigenvalues.
4. **Step4:** Verify the study’ consistency by comparing the predefined judgments to two factors: the Consistency Index (CI) and Consistency Ratio (CR) \[24\]:

\[
CI = \frac{\mu_{\text{max}} - n}{n - 1} \tag{7}
\]

Where \(\mu_{\text{max}}\) is the adequate eigenvalue to the pair-wise comparison matrix \(N\) is the set of elements that are considered for the study. CR is calculated by the following equation:

\[
CR = \frac{CI}{RCI} \tag{8}
\]
Fig. 4. The neural network process

Table 2. Criteria importance meaning.

| Relative importance | Meaning                          |
|---------------------|----------------------------------|
| 1                   | Equal                            |
| 3                   | Weak                             |
| 5                   | Strong                           |
| 7                   | Demonstrated over the others     |
| 9                   | Absolute                         |

RCI [25] is the random values of CI according to the number of criteria(n) as shown in Table 3.

Table 3. RCI values.

| Criteria number | RCI values |
|-----------------|------------|
| 1               | 0          |
| 2               | 0          |
| 3               | 0.58       |
| 4               | 0.90       |
| 5               | 1.12       |
| 6               | 1.24       |
| 7               | 1.32       |
| 8               | 1.41       |
| 9               | 1.45       |
| 10              | 1.49       |

The generated weights have been exploited to show the importance of each criterion and inputs for CNN. Figure 5 depicts the proposed model. The novel model is based on two major phases: the first one consists of generating the weights that will be exploited by CNN to classify the patients.
4 Our Illustrative Example and Discussion

COVID19 has been characterized by various criteria such as Fever, patient localization, and the age of the studied patient. To give a real classification, we have exploited the process of the multi-criteria AHP tool to determine the weight of each criterion. Our decision problem consists to classify a set of patients into a positive class and negative class.

Table 4 illustrates the decision matrix that corresponds to our decision problem, where the importance of the different criteria are determined. To validate these values, we have calculated the consistency that gives consistent matrices because each consistency rate is less than 0.1.

| Criteria | C1 | C2 | C3 |
|----------|----|----|----|
| C1       | 1  | 5  | 7  |
| C2       | 0.20 | 1  | 3  |
| C3       | 0.14 | 0.33 | 1  |

The normalized matrix is given in Table 5:

| Criteria | C1   | C2   | C3   |
|----------|------|------|------|
| C1       | 0.74 | 0.78 | 0.63 |
| C2       | 0.149| 0.157| 0.27 |
| C3       | 0.10 | 0.05 | 0.09 |
The next step concerns the generation of the different weights of the criteria considered for this study. After calculating such weights, we found that $C_1 = 0.72$ and $C_2 = 0.19$ and $C_3 = 0.08$. To prove the validity of this step, we have calculated the CR value. The weighted matrix is given in Table 6:

| Criteria | $C_1$ | $C_2$ | $C_3$ |
|----------|-------|-------|-------|
| $C_1$    | 0.72  | 0.96  | 0.57  |
| $C_2$    | 0.14  | 0.19  | 0.24  |
| $C_3$    | 0.10  | 0.06  | 0.08  |

$\Lambda_{\text{Max}} = 3.05$ $CI = 0.027$ $CR = 0.047$ After calculating the different weights by the use of the AHP tool, we use these generated weights to calculate the inputs of the neural network to convert data to image format. To do that, we have calculated the correlation Matrix $M$, the correlation vector $L$, and the reordering matrix $O$ as follows:

$$M_{j,k} = \frac{\sum_{c=1}^{N} (x_{c,j} - f_j)(x_{c,k} - f_k)}{\sqrt{\sum_{c=1}^{N} (x_{c,j} - f_j)^2}} \sqrt{\sum_{c=1}^{N} (x_{c,k} - f_k)^2}$$

where $f_j$ is the means of the feature $j$ and $f_k$ represents the means of the feature $k$.

$$L_{1,j} = \frac{\sum_{c=1}^{N} (x_{c,j} - f_j)(y_c - \bar{y})}{\sqrt{\sum_{c=1}^{N} (x_{c,j} - f_j)^2}} \sqrt{\sum_{c=1}^{N} (y_c - \bar{y})^2}$$

where $\bar{y}$ represents the mean of label.

The next step concerns making the classification of the group of patients using the CNN process.

Figure 6 shows the results of the classification. We remark that the proposed hybrid AHP-CNN model permits us to affect a diagnostic of patients by the classification of the patients in two classes: the positive class and the negative class. The main objective of this work is to classify the set of patients into two classes: COVID+19 or COVID-19. The patient is classified into the positive class according to the values of each criterion. This result allows us to make initial diagnosis, the advantages of this model: the rapidity of diagnostic, and minimizing the risk by avoiding contact between the patients and the hospital staff, make the maximum diagnostic of the patient in a short period from a far distance.
To study the sensitivity analysis of the proposed model, we have calculated the accuracy for three cases. Table 7 summarizes the different cases. We present the different results of accuracy for the three cases.

Table 7. The weights of cases.

| Cases | C1   | C2   | C3   |
|-------|------|------|------|
| Case1 | 0.72 | 0.19 | 0.08 |
| Case2 | 0.19 | 0.72 | 0.08 |
| Case3 | 0.08 | 0.19 | 0.72 |

Table 8 shows the values obtained for accuracy for each case:

Table 8. The accuracy of cases.

| Cases | Accuracy |
|-------|----------|
| Case1 | 88%      |
| Case2 | 87.8%    |
| Case3 | 87.75%   |

Fig. 6. Patient classification
5 Conclusion

COVID19 has upset humans’ life because of its rapid evolution. This imposes our real interest to overcome this horrible situation. CNN has shown its efficiency on several problems of classification such as the healthcare system. Motivated by the results obtained by CNN in the context of the classification, we have interested to use it to classify the patients infected in COVID’19. Several studies have been directed to solve this critical problem. However, the situation requires more effort from the research community. In this work, we have proposed the use of a hybrid AHP-CNN tool for making the patient classification. This novel strategy is composed of two phases. The first phase consists of finding the adequate weights of the essential criteria. Then, the second phase focuses on making the classification of a group of patients using the process of CNN. This work results proved the efficiency of the combined model.

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