

Artificial Intelligence-Based Medical Image Classification using a Multilayer Fuzzy Approach

KISHORE KUMAR AKULA[1], ALEXANDER GEGOV[2,3], FARZAD ARABIKHAN[2]
[1]Statistics eTeachers Group,
Royal Statistical Society
2110, 100 Leeward Glenway, Toronto, Ontario, M3C 2Z1,
CANADA

[2]School of Computing,
University of Portsmouth,
Winston Churchill Ave, South Sea, Portsmouth PO1 2UP Portsmouth,
UNITED KINGDOM

[3]English Faculty of Engineering,
Technical University of Sofia,
Sofia 1756,
BULGARIA

Abstract: - A Convolutional Neural Network (CNN) is an effective Artificial Intelligence (AI) technique for the automation of image analysis. However, to achieve a high level of accuracy, a CNN usually requires a large amount of data and a long training time. The current study addresses the above problem by proposing a novel AI technique. The latter can detect and classify abnormalities in images using a small amount of available data and a short training time. The proposed technique, Artificial Intelligence Based Medical Image Classification Using a Multilayer Fuzzy Approach (MFA), was validated using open access medical image data, where an image with a particular type of abnormal object contained in it was compared with a normal image with the same object in it. The similarity was then computed in percentages and subtracted from the hundred, which is the abnormality in the first image. The results showed that the novel MFA outperforms significantly better than the benchmark, CNN, and is a useful tool for automated analysis of medical image data sets.

Key-Words: - Multilayer fuzzy, convolutional neural network, image, training, classification, CT scan.

Received: July 2, 2022. Revised: August 19, 2023. Accepted: September 22, 2023. Published: October 25, 2023.

1 Introduction

To find abnormalities within objects in images, normally the experts in a particular field visually examine them. Medical diagnosis often requires visual examination of diagnostic images to find any abnormalities within the images. For instance, doctors examine CT scans to determine if cancer exists or not. Automation of the image analysis process would greatly cut down the time required to arrive at a diagnosis. Several methods have been developed since the rise of the field of Artificial Intelligence (AI) that rely on concepts from cognitive science.

1.1 Cognitive Science

Cognitive science is the study of the mind and its processes, such as learning, which contains sub-domains like knowledge, understanding, analysis, synthesis, and evaluation. The sub-domain of evaluation includes the process of comparing, [1]. Comparing two images to find their similarity is the key approach of this study. For example, when two objects in a CT scan like two images of lungs are compared, then the similarity or dissimilarity can be determined. When one normal image of the lung is compared with an abnormal lung image, then the difference is the abnormality. However, many precautions must be taken to ensure accurate comparisons and to extract the true abnormality, which will be discussed in the forthcoming sections.

1.2 Convolutional Neural Networks

The contemporary method used to find abnormalities in the objects of images utilizes one of the architectures of deep learning, which is a convolution neural network (CNN). CNN is used as a method for automatic, accurate, and reliable image analysis, [2].

The CNN finds patterns in images and then helps classify the images. In most of the literature where CNN has been used, abnormalities in objects within images cannot be found directly, but the model has to be trained with large data sets containing images in which the abnormality has already been identified and classified by humans. However, to get categorized data to train and test is a laborious process. Furthermore, if the data and categories are changed, then the software code has to be changed again.

The data size required for CNN is typically large. However, literature has shown that there are CNN techniques capable of utilizing small datasets, as demonstrated in, [3], [4], [5]. Nevertheless, it should be noted that even these small datasets often consist of hundreds or thousands of samples. In contrast, the MFA approach utilizes a mere 21 images for all steps, including the training, testing, validation, detection, and classification of abnormalities.

For example, if cancer needs to be identified and classified into one of several types of tumors using CT scan images, a CNN does not directly identify the cancer in the images to classify the cancer types. To do so, the CNN has to be trained with data in which cancer has already been identified, as well as images from healthy individuals without cancer.

This research proposes an AI-based method as an alternative that can bypass some of these challenges by using a Multilayer Fuzzy Approach.

1.3 Computer Vision

Computer vision is an interdisciplinary science to gain micro and macroscopic understanding of an image. It provides a straightforward and meaningful description of real-world objects from images and involves digital images or medical scans. Computer vision deals with images in terms of pixels, and its features include image processing, feature extraction, and cropping images. Additionally, computer vision techniques like structural similarity (SS) help with comparing two similar images like CT scans of lungs from two patients. Using this technique, it is possible to find the similarity or differences among the images in terms of a percentage or a fraction.

1.3.1 Image Comparison

An image has a fuzzy nature since it is a two-dimensional projection of a three-dimensional real object, [6]. Images are used in many scientific fields like geography, medicine, social sciences, and psychometrics. While it might be used to find water resources in the field of geography, it can be used to analyze CT scans, X-rays, and MRI scans, to study a pathological problem, a cancer tumor, or an infection in the field of medicine.

Images for medical sciences are typically standardized with a specific setup, angle, and other technical arrangements. For instance, a CT scan of the chest to detect a lung cancer tumor is acquired using the same settings. All images are taken from approximately the same side of the object in the image, like for instance, the front view of lungs. In addition, images of the same kind of object are acquired, such as the lungs or the brain. All images are also taken with the same lighting and intensity, covering approximately the same area. Furthermore, the images can be microscopic or macroscopic but not mixed.

1.3.2 Pixels

Each image is represented by units known as pixels. Additionally, an image can be represented as an image function, which, in turn, is the mathematical representation of an image. The image function is a vector-valued function consisting of a small number of arguments. The digital image is a special case of an image function, [6]. Once an image is represented as an image function, many of the statistical and mathematical concepts can be applied. These pixels are also considered to be fuzzy numbers.

1.3.3 Grey Scale Image

Generating a grey-scale image is a process in which each pixel of the image is represented by only the intensity information of the light. The colors of the image are black, white, and grey.

1.3.4 Structural Similarity Index (SSI)

The SSI is obtained when two similar images are compared, and this parameter reveals the percentage similarity between the two images, [7]. When more than 2 similar images are compared, then we get a structural similarity score. Several software like MATLAB, Python, and CRAN-R can be used to determine the SSI. The software will divide the parts of the images into sub-frames and compare them to find the similarity between one image and the next. Python was used in this study.

1.4 Fuzziness

In many real-world situations, information is not always clear-cut or binary. Instead, it allows for the representation and manipulation of vague or ambiguous data.

1.4.1 Fuzzy Set

The fuzzy set that will be used in this study is '{ID, Similarity percent},' where ID is the identification of the image and similarity percent is the similarity obtained when two images are compared. Along with fuzzy sets, both cognitive science and computer vision can be used to form an AI technique that can be used to detect an abnormality in the objects of an image by comparing images with normal objects in it and a similar image with abnormal objects in it.

The images must be acquired using a uniform set of specifications mentioned in the following sections, and the images can be from any of the sciences or social sciences. Using this technique, abnormalities in a massive number of images can be found. Furthermore, there is no need for data with identified and categorized abnormalities to train the process.

1.4.2 Multilayer Fuzzy Notion

The multilayer fuzzy system is based on some of the theoretical concepts from, [8], [9]. In particular, two layers are used which implement each of the two consecutive stages in image manipulation described below. The notion of a multilayer fuzzy set is being introduced in this study. An image is a two-dimensional projection of a three-dimensional object. A three-dimensional object has length, width, and thickness or height, whereas a two-dimensional object only has length and width. When an image is acquired, whether it is a CT scan or a normal photograph, the three-dimensional nature will be converted to a two-dimensional nature. That is, the projections assumed from the edges of a three-dimensional object will create a two-dimensional object. This creates a fuzzy notion in an image in computer vision, [6]. In addition to this fuzzy quality, a second fuzzy quality can be attributed to the pixel, which is the conversion of a continuous picture into a digital format, which involves fuzziness. Thus, digital images consist of pixels that are viewed as fuzzy numbers. Additionally, to run some computer vision commands, the conversion of a color image to a grey scale is needed, and this process involves fuzziness. Consequently, when a study deals with images, these images can be described by multilayer fuzziness, forming a multilayer fuzzy input, which will herein be referred to as the multilayer fuzzy notion.

1.4.3 Multilayer Fuzzy Set

As mentioned above, digital images fall under the multilayer fuzzy notion. Additionally, when two images are compared, the SSI will be obtained, which also possesses a multilayer fuzzy nature. In this study, the SSI will be equal to the membership value and the multilayer fuzzy set will be of the form, '{Identification of the image, SSI}.' For example, the multilayer fuzzy set when one CT scan of the lungs of a normal or healthy individual is compared with a CT scan of the lungs of a patient with some disease can be, '{patient ID = 111, SSI = 0.089}.'

1.5 Rationale for the study

Many hours are spent by medical personnel on disease diagnoses that could be spent on other patient care activities. The use of cognitive science concepts can be applied to aid in such diagnoses while also improving the test-retest reliability. However, the caveat is that existing methods, such as CNNs, require a large data set and a separate data set that has already been categorized as having the abnormality being studied, which makes this procedure less effective for analyzing diagnostic images of new or rare diseases that have less data. Furthermore, even with established technology, it may be difficult to obtain a data set large enough to train the program. Fuzzy systems can bypass some of these issues since they do not require a training data set, and the minimum number of images required to make a comparison is two, making it easier to make comparisons with a limited number of images.

As an application of the method developed in the current MFA study, the medical field was chosen. Specifically, the application will focus on the identification of COVID-19 infection and categorization based on the spread of the disease as seen on the CT scan. Using the MFA method, a normal image is sufficient to compare other images to detect whether abnormalities exist. Moreover, this is the first time that abnormalities will be found by comparing an image with ‘good’ objects, such as healthy tissue, and images with objects with abnormalities, such as tissue infected with a virus.

2 Problem Formulation

2.1 Primary Aim

The primary aim of this research is to develop an AI-based MFA using computer vision and a small data set that can detect and classify accurately abnormalities in medical images within a fairly short training time.

2.2 Secondary Aim
The secondary aim is to apply MFA to a small data set of 22 images of healthy and COVID-19-positive lung CT scans, [10].

3 Problem Solution

3.1 Approach for Primary Aim
An image with a normal object in it and several other images with the same type of object, but with abnormalities, were considered. The normal image was compared with the abnormal images one by one, and each time, the structural similarity index (SSI), [8], score was calculated. In this case, the SSI score is a percentage-based fraction representing the level of abnormality of the objects in the images. After finding the SSI for the images, several techniques, including a multilayer fuzzy system, other computational intelligence methods, and software code testing tools, were used to detect and classify the images.

3.2 Approach for Secondary Aim
MFA was used on a data set of CT scans of normal right lung images andCOVID–19–confirmed images.

3.3 Images
MFA can be implemented for any image, such as, for example, pathological images, a geographic region, or an astronomical image, as long as they are acquired from the same angle and the same frame dimensions. However, in MFA, the focus will be on medical images for the application part of the primary aim.

3.4 The Data Set
The data set for the application of the study method, MFA, was acquired from the National Cancer Institute, [10], and the data sets were downloaded by checking the option titled, 'COVID.' The images were a mix of COVID-19-positive, as well as normal images, the latter of which were CT scans without any abnormalities. A total of 21 images were used, of which normal and COVID-19-positive images were present. Among these 21 images, a few CT scans had high contrast. Out of all the images, one normal CT scan was taken as the standard image. As there is no training or testing process, the number of images with and without COVID-19 is independent of finding the abnormality in the images. The minimum number of images required to test abnormality using the MFA method is two: one normal image which is the standard image and one image being tested for an abnormality. To classify images, any number of images can be considered other than the normal image, without an upper or lower limit for the number of images.

3.4.1 The Prediction Data Set
The prediction data set consisted of 21 randomly selected CT scans, [10], that were acquired to investigate COVID-19.

3.4.2 Standard Image
A standard or normal image is a reference image with which the other images under study will be compared. Both the standard image and other images under study are of the same file type (e.g., .dcm, .jpg), and have the same contrast, brightness, and cropping as the image in Figure 1(1.1). Even with different brightness or contrast (like the images in Figure 1(1.1) and Figure 1(1.2) the MFA method works, but it takes a greater amount of time to find the similarity values.

3.4.3 The Images under Study
The standard image and the images being studied will be of the same kind. This is because to study diagnostic problems in the lungs, the standard image, as well as the images under study, should be images of lungs acquired with the same specifications, such as medical CT scans. Some examples of images with different contrast levels that are cropped at different places are shown in Figure 1. Images like this with different amounts of space in the background or images that are cropped at different levels will yield more biased comparisons.

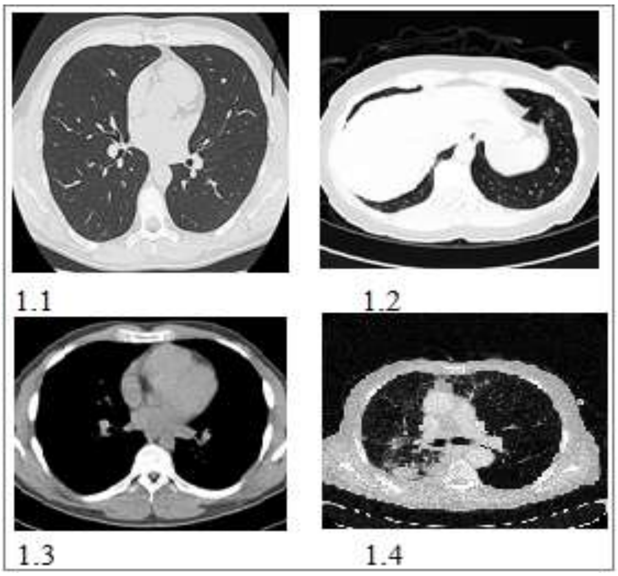

Fig. 1: Human lung CT scans with various diagnoses:
1.1 - A normal lung CT scan acquired at normal contrast and cropped at the lungs,
1.2 - a CT scan of COVID-19-positive lungs, cropped at the lungs,
1.3 - Normal CT scan with high contrast and not cropped at the lungs,
1.4 - Low contrast, normal CT scan for lungs – uncropped at the lungs.

3.4.4 Sample for Application

To study an application of the MFA method, the method was applied to a small data set of CT scans of adult male and female lungs. The data considered were of a mixed sample with confirmed COVID-19 cases and normal CT scans without COVID-19.

3.5 Usage of Computer Vision

3.5.1 Grayscale of the Image

To get a good estimation of the SSI, all the images were converted to greyscale. This allows for the focus of the image to be on the intensity of light rather than the color of the image. To accomplish this, all natural colors of the image were converted to a shade between black to bright white.

3.5.2 Similarity between Two Images

When two similar images are compared, like CT scans of the lungs of two humans, the images will be similar by a certain percentage, which is denoted by k%.

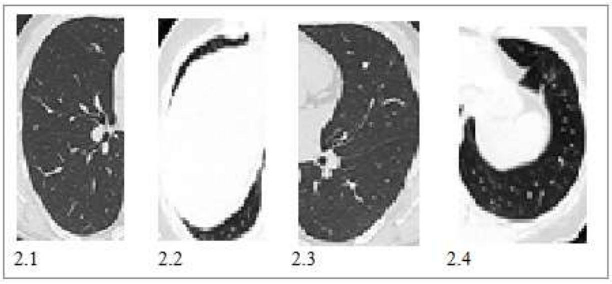

Fig. 2: Cropped images of CT scans so that only the left or right lung is included.
2.1 - A normal left lung,
2.2 - an infected left lung with COVID-19,
2.3 - a normal right lung,
2.4 - an infected right lung.

3.5.3 Noise

In the context of MFA, the noise is considered something that affects the similarity between two images when compared. That is, some regions of an image may contain too much contrast or other parts of the objects that we do not want to consider. For instance, if the goal is to only study the CT scans of lungs from two individuals, then the presence of bone in the image will influence the similarity score. In addition, when two images are compared there might be similarity due to grey pixels and dissimilarity due to the presence of unwanted objects in the background. This noise cannot be completely avoided, but it can be minimized if the object of focus in the image is cropped and extracted before comparison. For instance, in the application part of MFA, instead of taking an image consisting of both the left and right lung of a human and comparing it with another image of both lungs from other humans, the left lung and right lungs will be cropped and compared separately with the corresponding left or right lung images of other individuals. Panels a and c in Figure 2 show examples of the normal right and left lungs, respectively. Images b and d are the right and left lungs infected by COVID-19.

3.5.4 Structural Similarity Index (SSI)

The main technique used in the study is SSI from computer vision. This technique is used to compare two similar structures or objects present in an image and find the percentage similarity of the first image to the other. The SSI can be found using the following formula, [7]:

$$\textbf{SSI (x, y)} = \frac{(2\mu_x\mu_y+c_1)(\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}$$

Here, **x** and **y** are two image patches of the same spatial location of two images being compared and whose SSI is to be calculated. μ_x is the mean of **x**, μ_y = mean of **y,** σ_x^2 and σ_y^2 are mean and variances of **y,** and σ_{xy}^2 is the covariance of **x** and **y**. Each part of the first image will be compared to the corresponding part of the other image, provided that the images are of the same dimensions and the location of the object in the two images is approximately the same.

The SSI between two images works in such a way that all parts of one image (x) will be compared with the corresponding parts of a similar image (y), pixel by pixel. When two images are compared, the minimum SSI is 0% if the images are dissimilar, and it is 100% if the image is compared to itself. However, under no circumstances will the SSI be equal to 0. The reason for this is that shapes, as well as white, grey, and black pixels, are present in any image. Consequently, most images will have an SSI that is a real number ranging from 0 and 1.

3.5.5 Acquiring the SSI between a Single Standard, Normal Image Versus Multiple Images with Abnormalities

The method formed to get SSI is shown in Figure 3. The standard image will be compared to images with abnormalities but are the same type of image and the same spatial location of the same image. With this method, the similarity between two images will be obtained as a percentage. One characteristic of the SSI to be noted is that no two images of the same kind are 100% alike, because of the difference in the objects in the images. For example, even if two healthy lungs are compared, the SSI will not be 100%. The reason could be the size of the healthy lungs, the unmatched color of pixels of the object or background, or the difference in the ages of the persons, among other factors.

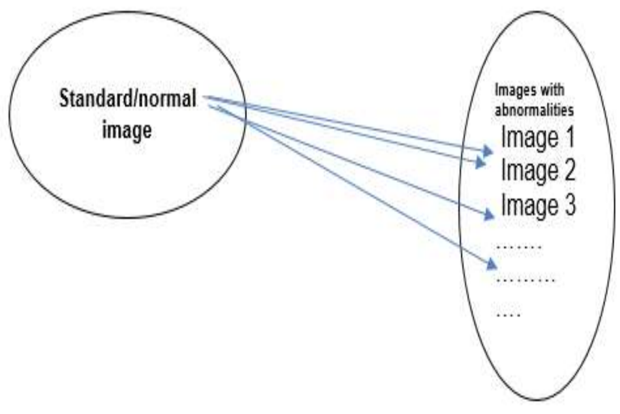

Fig. 3: A schema of how normal or standard images are compared one by one with images containing abnormalities, such as a tumor or infection.

The general instance of this relationship is as follows:
If SSI = 0%, then the abnormality among the images =100% approximately

If SSI = k_1%, then the abnormality among the images = (100% - k_1%) approximately

If SSI = k_2%, then the abnormality among the images = (100% - k_2%) approximately

If SSI = k_3%, then the abnormality among the images = (100% - k_3%) approximately

If SSI = k_n%, then the abnormality among the images = (100% - k_n%) approximately, where k is an unknown arbitrary constant. To find the value of k, the rules based on intelligent systems were used.

3.6 The Multilayer Fuzzy Input

As mentioned previously, the first type of fuzziness in the image is due to the conversion of a three-dimensional real object to a two-dimensional image. In addition, the second type of fuzziness results from the formation of pixels in the image. Together, the multilayer fuzzy input (Figure 4) consists of the images to be studied, such as the CT scans shown in Figure 1 and Figure 2.

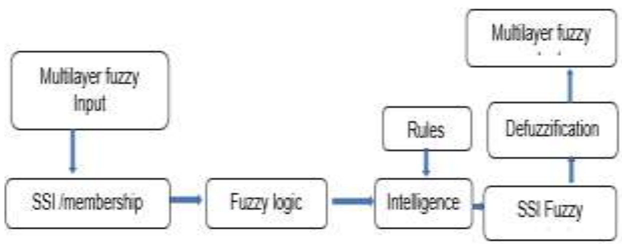

Fig. 4: Flow of the algorithm used in MFA.

3.6.1 The Multilayer Fuzzy Set (DFS)

The multilayer fuzzy set of abnormalities in the images is given by 'DFS = {ID, μ(ID)},' where ID is the identity of the image or patient, and μ = SSI, is the membership input. For instance, in the application part of MFA, the multilayer fuzzy set is '{patients ID, {2.3,0.01, 1, …..}}.'

3.7 Defuzzification, Applying Fuzzy Logic, Intelligence Rules, and Classification of Images based on the Intensity of Abnormality in the Images with Respect to SSI

The abnormalities in the objects of the images are represented by the SSI score given by the membership function of DFS, which is a crucial step

in the current MFA project. After testing the code several times with the data, the numerical values of k will be decided by checking the images and the SSI score. As a result, the images will be classified based on the intensity of similarity using fuzzy logic in this MFA study as follows.
If SSI ≤ or ≥ k_1%, if 'Yes' then the abnormality within the image is 'severe', or if 'No':
If SSI ≤ or ≥ k_2%, if 'Yes' then the abnormality within images is 'moderate', or if 'No':
If SSI ≤ or ≥ k_n%, if 'Yes' then the abnormality within images is 'none'.
This logic scale can be chosen after testing the software code with the data. After applying the above steps, the data will be automatically classified according to the severity of the abnormality.

3.7.1 Numerical Value of k

MFA will be applied to the data set of CT scans of lungs mentioned above, to investigate infection with COVID-19. As part of that, when the normal right lung (Figure 2(2.1)) was compared with an abnormal image of the right lung (for example, Figure 2(2.2)), then a numerical value for k in the above schema will be obtained.

3.7.2 Rules based on Intelligent Systems and Computer Vision that Help to Find the k Values

The rules required to help find k values are the most crucial stage of the MFA study and are given below.

a. Manual software testing (MST). MST is a process in which the software code or package written will be tested to determine whether it is correctly fulfilling its tasks, and specifications and acquiring accurate results. To do so, a clear testing strategy will be created. Subsequently, the code will be executed several times, and the accuracy of the results will be tested. If the accuracy is not satisfactory, then the code will be corrected and run repeatedly until the correct results are obtained.
In MFA, MST helps find the bounds of the SSI for classification of the severity of the disorder in the objects of the images. The main rule to find k values involves testing the code and adjusting the k values. Here the value of k is equal to the SSI. For instance, if SSI is 10%, then the abnormality in the objects of the image is severe. In addition, if the SSI is greater than 10% and less than 45%, then the objects in the image will be normal. Each time the crucified and classified images are examined, the k value will be adjusted accordingly.

b. Outliers. Sometimes the software shows greater similarity or dissimilarity between images than is the case. This is due to the presence of grey/black pixels in both images or more contrast or less brightness in the images. The outliers cause false similarity or false dissimilarity when two images are compared.

c. The characteristics of the image. Knowing about the characteristics of the images being studied will increase the accuracy of the k values. For example, since the images considered are CT scans of the lungs, information about how the scans were taken, like the angle, contrast, and brightness, is important. Furthermore, using the same example of CT scans, the heart is anatomically located approximately between the lungs. If an observer who is not a medical professional were to examine the images, the heart might seem like a tumor or an infection due to COVID-19.

d. Precautions to be taken to find k values.
i. The size of all images must be the same.
ii. To improve the accuracy of the SSI score, the object under study in the images has to be cropped at the same point as shown in Figure 1(1.2) and Figure 1(1.4), so that only the lung tissue will be compared to lung tissue and not blank space within the image.
iii. The accuracy of the results can be improved by using images with the same contrast and brightness.
iv. It is better to crop the unwanted part of the image and keep only the required object.

3.7.3 Defuzzification and Multilayer Fuzzy Output

The images were gathered in terms of SSI based on the SSI fuzzy output. The images were classified using their SSI score, and the classified images were in the form of the fuzzy score, SSI. Each class is a subset of the original fuzzy set, '{ID, μ(ID)},' and again, each of these subsets are multilayer fuzzy set.

3.7.4 Multilayer Fuzzy Output

Figure 6 is a sample of the actual images being considered for the study, which were categorized with respect to the abnormality.

3.8 Prediction with Random Data

A total of 9 images from a different database, [10], were considered to test if the MFA model was working correctly or not, and whether it was able to make accurate predictions. To check the model, the data for the prediction was linked to the software code, and the code was run.

3.9 Software

The software used was Python 3.6.1 of Anaconda3 4.4.0 with Spider 3.1.4 as the graphical user interface.

3.10 Efficacy of the MFA Method

The efficacy of the MFA method was examined by considering the CT scans of the same patient taken at different times. Since the patients developed COVID-19, when the CT scans were observed, the spread of the virus can be seen gradually (Supplementary Figure 1). For the same scans, the SSI was calculated just to check whether the SSI score was inversely proportional to the spread of the virus and whether it gradually decreased with the spread of the disease.

3.11 Results and Discussion

In the current study, the multilayer fuzzy method, MFA, was developed using fuzzy systems, along with the concept of comparison derived from cognitive science and SSI from computer vision. The application of the MFA method will be to detect the presence or absence of COVID-19 in CT scans of the lungs and classify them according to the spread of COVID-19 as seen on the CT scans.

3.12 Cognitive Comparison using Computer Vision to Detect COVID-19 at a Microscopic Level

The way comparisons were carried out using computer vision is shown in Figure 5 using a normal CT scan versus the CT scan of a lung affected by COVID-19. Every spatial region of the normal image was compared to the corresponding spatial region of COVID-19-positive CT scans. The difference is the spread of COVID-19 and noise if any.

3.13 SSI Scores and a Multilayer Fuzzy Set

The SSI scores when the normal right lung CT scan was compared with the abnormal right lung affected with COVID-19 are given in Supplementary Table 1.

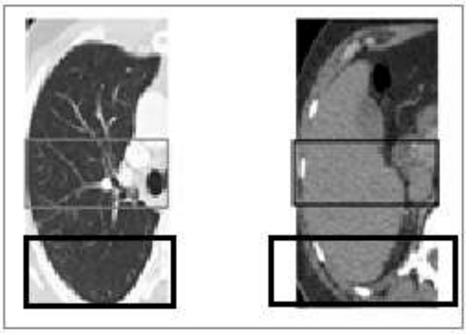

Fig. 5: The method used to find the SSI score. SSI was calculated for a normal CT scan of a lung versus a CT scan of a COVID-19-positive lung using the same spatial location and utilizing the cognitive science concept of comparing.

3.14 The Multilayer Fuzzy Set for the Application of the Current Method, MFA, to Detect COVID-19 in CT Scans

An example of the multilayer fuzzy set for the left lung CT scans is {ID, SSI(ID)} = {(1, 0.5602), (2, 0.282), … (n,1.00)}, where ID is the patient's ID, and SSI is the membership value. Another example of a multilayer fuzzy set for COVID-19-positive lungs categorized as having a severe spread of the virus is given by {ID, k_2}, where k_2 represents the SSI scores, a cut-off for the severe abnormality.

3.15 The Detection, Classification, and Prediction of COVID-19 using MFA

3.15.1 SSI or k Values Found when the Normal Right Lung is Compared with the Data

After testing the code several times with the data of CT scans and adjusting the k value according to the abnormality, the following categorization was established:

SSI or $k \leq 0.2000$, for a very severe abnormality,

$0.2000 < \text{SSI or } k \leq 0.2800$, for a severe abnormality,

$0.2280 < \text{SSI or } k \leq 0.3030$, for a moderate abnormality,

SSI or $k \geq 0.3030$, for a mild or no abnormality.

The classification by considering the above thresholds after testing the code several times is shown in Table 1 and some of the classified images are shown in Figure 6. Although the images in Figure 6(6.3) and Figure 6(6.4) look alike, the classification for both is different using MFA, since the image in Figure 6(6.3) has higher contrast than the image in Figure 6(6.4).

Table 1. In a random data set of CTs, COVID-19 was successfully detected and classified according to the severity of the spread of the virus by MFA.

Right lung CTs detected & classified by the degree of COVID-19 infection by MFA				
Total CTs	**Very severe**	**Severe**	**Moderate**	**Mild or Normal**
21	7	5	2	7

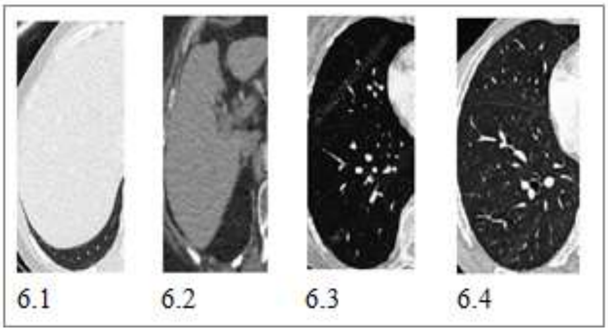

Fig. 6: Detection and categorization of COVID-19 with the help of multilayer fuzzy systems**.** The left lung has been cropped and compared with the normal left lung and categorized as

6.1 - a very severe abnormality,
6.2 - severe abnormality,
6.3 - moderate-severe abnormality (however, this is due to high contrast) and,
6.4 - mild or normal CT scans.

3.16 Efficacy of the MFA Method

The results from testing the efficacy of the MFA method (Supplementary Figure 1 with CT scans and the SSI scores) were derived from a single patient with COVID-19. The CT scans were taken with a time gap between each image. The propagation of the virus in the lungs was gradual as seen in the CT scans. The scans with the SSI are shown in Supplementary Figure 1. The CT scan in the first figure panel showed greater spread of COVID-19, with an SSI of 0.078, whereas the CT scan with less spread of the virus had a greater SSI of 0.2659.

Using the multilayer fuzzy set, every spatial location of an abnormal object within an image can be compared to the corresponding spatial location of a normal object (Figure 4). This process generates the SSI, which represents the abnormalities of the objects in the image. This is a feature of the MFA study when contrasted with the current comparator, a CNN, the latter of which cannot find the abnormality in the images directly but needs to be trained and tested using an already categorized data set with abnormalities. Moreover, using the MFA method, once the thresholds for different abnormalities are found, the image can be categorized automatically (Section 4).

In addition, the same analysis carried out by a physician to recognize abnormalities in a CT scan can be performed using MFA. Moreover, the physician would need time to decide that the CT shows an abnormality, whereas the present method can diagnose numerous CTs for abnormalities in a shorter time frame.

3.17 The MFA Method Versus the CNN

3.17.1 Training, Testing and Validation by a CNN using the Considered Data Set, as well as Prediction

To further validate the MFA method, it was contrasted with the most recent comparator, a CNN. The same data used in the previous section to test the MFA method was not large enough to run a CNN. The training showed 100%, but the validation accuracy was 0%. In addition, in the further epoch, the validation fluctuated between 0% and 100% percent, showing the insufficiency of the data. However, with the same data, the detection and classification of the abnormality of COVID-19 was not only possible but also accurate using the MFA method (Table 1). The reason the MFA method works with less data and the CNN does not is that the MFA method is based on the comparison of two images, requiring only two similar images. On the other hand, a CNN has to be trained first, which needs a greater number of images to learn the patterns within the images. The predicted images from a random data set to examine the process of detection and classification of COVID-19 in the right lung using the inspection method are presented in Figure 7.

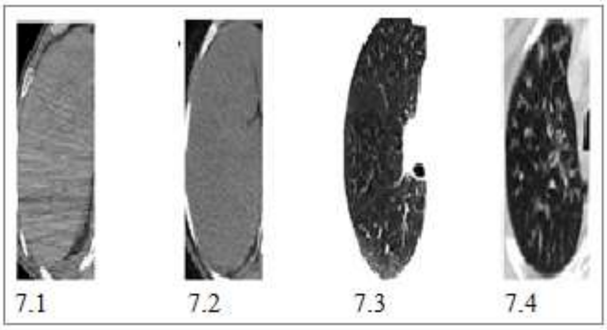

Fig. 7: Predicted images from a random data set to examine the process of detection and classification of COVID-19 in the right lung using the inspection method**.**

7.1 - a very severe abnormality (however, this is likely due to high contrast),
7.2 - a severe abnormality, and
7.3 - a moderate abnormality, and
7.4 - a normal lung.

3.17.2 Prediction Accuracy of MFA Versus the Current Comparator, CNN, using a COVID-19 Data Set

As the CNN needs a massive, already classified data set for training, the data considered was insufficient to run a CNN (Section 3.17.1). Subsequently, 21 random CTs were fed into the CNN, as well as into the MFA method. It can be observed in Table 3 that the CNN failed to predict the presence of COVID-19, whereas the classification and prediction by MFA were successful with the same small data set of CTs. Except in the case of a 'very severe' abnormality, all the CTs were correctly identified and classified according to the severity of the spread of COVID-19. The images categorized as having a 'very severe' abnormality contained high contrast, so these were outliers, as described in previous sections.

As seen in Table 2, CNN was not successful in classifying the images with regard to the abnormalities in the small data set used, as opposed to MFA which was quite successful. In addition, CNN usually has a long training time whereas MFA has a short training time.

Table 2. Comparison of predicted results for COVID-19 data.

	Categories of abnormality in COVID			
	Very severe	Severe	Moderate	Mild
No. Of CTs	9	10	1	1
MFA[a]	9 (100%)	8 (80%)	1 (100%)	1 (100%)
MFA[b]	0 (0%)	2 (20%)	0 (0%)	0 (0%)
CNN[a]	2 (22%)	0 (0%)	0 (0%)	0 (0%)
CNN[b]	7 (78%)	10 (100%)	1 (100%)	1 (100%)

[a.] Correctly classified, [b.]Misclassified

Under the very severe category, the correct classification by the current method MFA was 78% greater than the classification by the CNN. Moreover, under the severe, moderate, and normal categories, the CNN was not able to classify any data, whereas the accuracy was 80%, 100%, and 100% greater than a CNN in these categories, respectively, when classified by MFA. Similarly, the misclassification by CNN was several times greater than the MFA method, as seen in Table 3.

This comparison demonstrates that MFA works better than the current comparator, CNN, for classification, in part, because the CNN cannot detect the abnormality in images directly like MFA and needs already classified data.

Based on these preliminary tests, the MFA method was found to be accurate for even minor differences in the abnormality in the image, because the method is based on the comparison of a pixel in the normal image with a pixel in the corresponding spatial location in the image with a potential abnormality (Section 3.4.4).

Table 3. The difference between the MFA method and the current comparator, CNN, is in detecting abnormalities and classifying the abnormality for any kind of similar images.

	MFA	**CNN**
1. Data set size needed	small or massive	Massive
2. To find abnormalities in rare images	Successfully works on rare disease images	Cannot be used with rare images, as the sample size will not be large
3. Detection of abnormality in the objects of similar images	Detects abnormalities	Cannot detect the abnormalities
4. Minimum number of images needed to form the method	One (because it is to compare)	More - possibly thousands
5. Required, already classified images	Not required	Mostly Required

The MFA method showed a gradual change in the SSI score corresponding to the spread of the abnormality. For the application part of the present method, the longitudinal scans of a patient with changes in the spread of COVID-19 over time were considered. The gradual change in the spread of the disease (Supplementary Figure 1), as seen on the CT scan, resulted in gradual changes in the SSI score. For instance, the SSI score of the first image is 0.078 and the spread of the COVID-19 virus almost fully occupies the left lung, whereas in the last image, the infection is spread over a smaller area of the same lung of the same patient, with an SSI score of 0.2659. That is, the similarity between the normal image (healthy lung) and the first image was very low, compared to the similarity between the same normal lung and the last image. This shows that the MFA method can identify the abnormality in the image, like the current comparator, which is a CNN. MFA can also identify the rate of increase of the spread of the virus if the exact time between acquisitions of the two images is known, which the current comparator, CNN, cannot.

4 Conclusion

The proposed MFA is an interdisciplinary cross-application of AI with multilayer fuzzy systems, intelligent systems, and computer vision. This approach can detect abnormalities in similar images from any application domain and classify them by comparing a normal image with images containing a similar object with abnormalities. MFA does not require training and testing as compared with the comparator, CNN. The prediction accuracy of MFA for a small COVID data set was significantly higher than the one of CNN. That shows that MFA can work effectively even for small data sets and therefore can be used with data for rare or new diseases. Overall, the current study presents a method to convert the abnormality present in the objects of the image into a quantity or number.

Some of the future applications of this study are further use of the MFA both in the medical sciences, as well as outside of medicine. For instance, in the case of medical studies involving CT scans, an application of the current study would be the quantification of the abnormality in the lung resulting from cancer using disease images. As a future study, the risk due to the quantified abnormality that is present in a group of patients or a single patient can be estimated. Beyond medical sciences, this method can also be applied, for instance, to automatically analyze satellite images of regions of Earth containing water, or analyze astronomy images of space.

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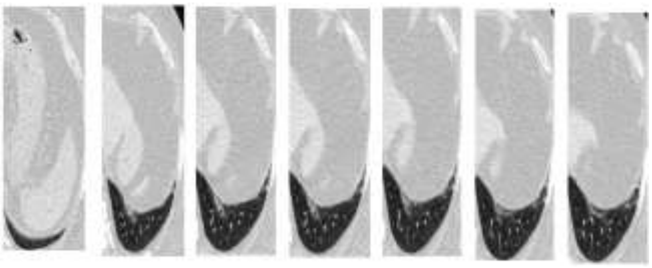
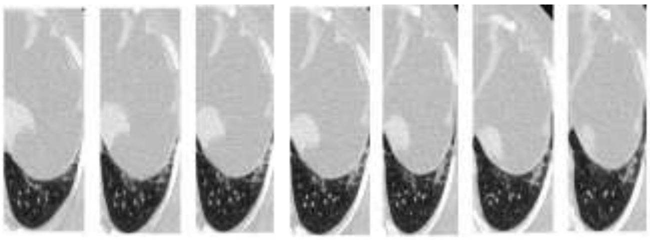
Appendix

Supplementary Table 1.
Abnormalities detected in the right lung

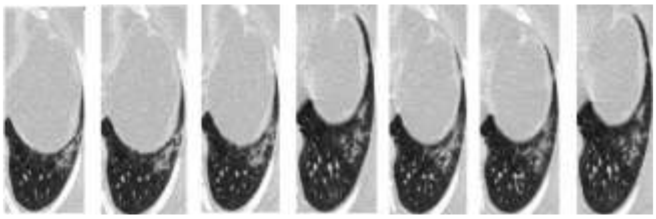
$k_1 <= 0.2$		$0.2 < k_2 <= 0.28$	$0.28 <= k_3 <= 0.303$	$k_4 >= 0.303$
0.1717,	0.1994,	0.2742	0.2873	1
0.1987,	0.1066,	0.2136	0.3015	0.3316
0.0916,	0.1654,	0.227		0.441
0.192		0.2064		0.421
		0.2081		
		0.201		
		0.221		
		0.2372		



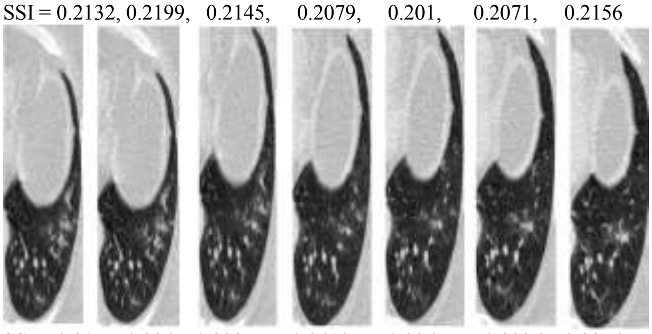
SSI = 0.078. 0.1957, 0.1924, 0.1893, 0.195, 0.1811, 0.1898



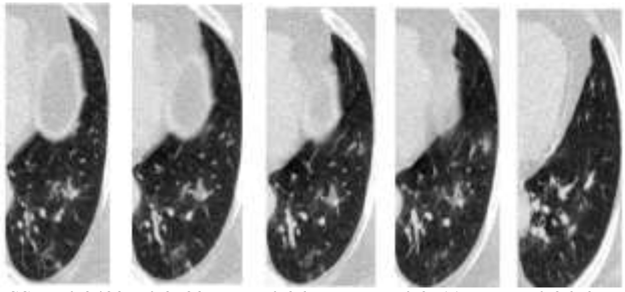
SSI = 0.1974, 0.212, 0.1935, 0.1892, 0.1884, 0.2023, 0.2115



SSI = 0.2132, 0.2199, 0.2145, 0.2079, 0.201, 0.2071, 0.2156



SSI = 0.2157, 0.224, 0.2335, 0.2419, 0.2365, 0.2326, 0.2354



SSI = 0.2423, 0.2523, 0.267 0.2711 0.2659

Supplementary Fig. 1: CT scans of the lungs of a single patient at different stages to detect **COVID-19.** This figure shows the efficacy of the MFA method at detecting abnormalities in the objects within an image using a multilayer fuzzy system, artificial intelligence (AI), cognitive science, and computer vision.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Kishore Kumar Akula conceived the study, wrote the software code, and prepared and reviewed the manuscript.
- Alexander Gegov supervised the idea and the research and reviewed the manuscript.
- Farzad Arabikhan supervised the research and reviewed the manuscript.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors do not have any conflicts of interest to disclose.