Aims and Scope

Aurum Journal of Health Sciences (AJHS – A. J. Health Sci.) is an international open access platform for basic, applied, theoretical and clinical studies in health sciences. AJHS publishes double blind peer-reviewed re- search articles, short reports, case reports, invited reviews and letters to the editor. AJHS is published trian- nually both in printed and electronic version. AJHS is a multidisciplinary journal on health sciences and ac- cepts manuscripts on dental, medical, health services and pharmaceutical studies. The manuscripts linking different disciplines of health sciences will be given a priority in the journal.

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Editorial

The fourth volume of Aurum Journal of Health Sciences (AJHS) is published in 2022 with a change in the editorial board. I would like to thank all the members of the previous editorial board, especially the Editor-in-Chief Dr. Gaye Hafez. I wish success to the new editorial board members of our journal.

In our new issue, we published original research topics in the field of health sciences. We issued four original articles in this issue. In the first article titled "Building an Electronic Health Portal With an E-Health Application to Communicate With Patients" the design and implementation of a common electronic health records system, which various clinicians and patients can access, is presented depending on the RBAC access control. The authors focused on creating a patient- specific password through PHP programming functions. According to the authors; it is also possible on this portal, to establish effective communication between the doctor and the patient, such as booking appointment electronically. Moreover, doctors can use the system to communicate urgent reports regarding the spread of newly discovered pandemics such as COVID-19.

In the second article titled "Detection of COVID-19 Pneumonia Effects in Chest X-Rays Using Deep Learning" an artificial intelligence tool is presented. The development of technological tools based on artificial intelligence could contribute significantly to the fight against COVID-19. In this paper, the authors proposed a deep learning based model for COVID-19 detection relying on the effects it yields on the lungs.

In the third article titled "Detection of COVID-19 in Low Energy Chest X-Rays Using Fast R-CNN", the authors presented a variation of convolutionary neural networks, which works extremely well on current data set — a customized architecture with optimal parameters. In their contribution, they focus on lowering the complexity of the network, while yet reaching a phenomenally high degree of accuracy. To achieve this aim, authors' model has been tailored for high performance and an easy design.

In the last article in this issue, "A New Method Based CNN Combined With Genetic Algorithm and Support Vector Machine for COVID-19 Detection By Analyzing X-Ray Images", a COVID-19 detection framework presented to detect COVID-19 by analyzing X-ray tests. The proposed framework based CNN combined with genetic algorithm and SVM classifier.

As can be seen, in this issue of our journal, the artificial intelligence based monitoring of the COVID-19 pandemic with computer applications was mainly discussed. All articles in this issue have been reviewed after careful review processes. We would like to thank all authors and reviewers for their valuable contributions.

Prof. Dr. Osman Nuri Uçan
Editor-in-Chief, Aurum Journal of Health Sciences

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RESEARCH ARTICLE

BUILDING AN ELECTRONIC HEALTH PORTAL WITH AN E-HEALTH APPLICATION TO COMMUNICATE WITH PATIENTS

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Abstract: Patients have better access to their healthcare records and resources thanks to e-health portals. We create and deploy an e-health portal that efficiently integrates a variety of background medical services. The most difficult aspect of implementing such a system is ensuring that essential security criteria are met, such as patient data confidentiality, diagnostic outcome accuracy, and healthcare service availability. In this study, the design and implementation of a common electronic health records system, which various clinicians and patients can access, is presented depending on the RBAC access control. We focused on creating a patient- specific password through PHP programming functions. It is also possible, on this portal, to establish effective communication between the doctor and the patient, such as booking appointment electronically. Moreover, doctors can use the system to communicate urgent reports regarding the spread of newly discovered pandemics such as Coronavirus. System testing and evaluation are also offered.

Keywords: E-health, EHR, RBAC, E-health portal.

1. Introductıon

E-health is characterized as the "use of information and communications technologies (ICT) in support of health and health-related fields. It Includes healthcare services, health surveillance, health literature, health education, knowledge and research" (Ngoma 2006), which has the potential to be extremely useful in delivering health care in a variety of settings. These systems have the potential to save lives and provide comprehensive data for strategic planning, especially in areas where hand- compiled data is often years out of date. The aim of Healthcare is to provide high-quality services to its clients.

Healthcare uses information and communication technology to improve the quality of services. The involvement of technology informatics in health aid in reducing human errors in healthcare. In today's e-health application, there are many IT software implementations in the healthcare sector. E-health is currently one of the pillars of health care reform and one of the leading research goals of many institutions, academics, and organizations. The following acronyms indicate some of the services that standard e-health systems provide:

i. EHR: an electronic file of a complete report on the patient's health that makes all information accessible to approved users instantly and securely. (Car et al. 2008).

ii. EMR: an electronic report containing the entire medical history of the patient (Walker et al. 2005).

iii. PHR: a health report in which the patient keeps track of his medical information in a personalized, safe, and confidential manner (Laxman, Krishnan, and Dhillon 2015).

iv. e-prescribing: a form of technology that allows a healthcare facility to write and deliver prescriptions to a pharmacy electronically. (Walker et al. 2005).

v. e-appointments: An online service making an appointment with any health organization quick and convenient, while also cutting down on wait time.

vi. m-health: a universal term that includes health-related activities It's used in cell phones and other wireless devices (Laxman, Krishnan, and Dhillon 2015).

vii. Telemedicine: providing health services and information remotely using information and communication technology (Maksimović and Vujović 2017).

viii. Telehealth: introduce health-related services and information by ICTs (Conrad 1998).

The paper aims to study the application of e-health by designing and implementing the electronic health portal. We highlight the electronic health record and the importance of interoperability. The main contribution is the design and implementation of an e-health portal through a three-tier architecture. We use the RBAC (Role-Based Access Control) model. In this portal, the patient can communicate with the doctor, store his health file, and refer to him/her at any time. We focused on patient data privacy and security by not allowing anyone to enter the system without permission by creating a highly secure password based on PHP programming functions. We also highlighted the portal's capability to communicate urgent reports of newly discovered pandemics, such as the Coronavirus.

2. Electronıc Health Record

The electronic health record describes all digital information technologies used in patient care. It is an electronic database that provides all the patient's health information, including personal data (Armstrong et al. 2007). EHR contain fewer errors and are characterized by high security with better time management and lower costs. As a result, it offers faster and more precise access to medical information.

2.1. Interoperability of EHR

According to ISA (International Standards Association), the EHR must contain information about care in a computer-readable form. Multiple users can securely access it. All the users have access to their medical records, except visitors who have not been granted permission. The longer-term goal is to assist with continued, qualitative, and practical health care (TR 2005). A patient may get care from several hospitals during his lifetime, so each of those facilities should be allowed to use his previous data without restriction (Huang and Yin 2012). Interoperability is possible to evaluate on three distinct levels: protocol, the system's behavior to the end-user, and the outcome (Eichelberg et al. 2005). HL7 (Health Level Seven) defines interoperability as Technical, Semantic, and Process (An 2011). From the technical point of view, the primary concerns are related to health data transfer and security. In the process of transmitting the data, both send and receive are done in a standardized manner. The semantic part is an integration based on both parties' relevance and take on the information sent back and forth. Semantic tools were applied to make the researcher's findings intelligible to the participant. Process part: operation interoperability focuses on a more holistic approach to data use that results in increased value (Arzt and Salkowita 2007). interoperability is difficult because the heterogeneous systems are already in place. Moving previously-stored patient data from one system to another is hard. Hospitals and healthcare facilities are unlikely to invest in a new EHRs because of the high cost of implementation. Also, the system's interoperability has its issues. Clinical information delivery can be provided at various locations, including medical clinics. A larger system requires a greater effort to put together. Medical sharing is possible with grid electronic interoperability. It is a combination of technical elements and semantic/ sexemtic using the HL7 Semantic Model. It can be used to represent the message's HL7 data. XML is mainly used to send information and use web systems as a platform for everything in GRID. The WSDL, UDDI, and XML help drive the Integration of various types of middleware using widely used protocols across different platforms utilizing commonly used protocols and standards such as HTTP and XML (Bilykh et al. 2003).

2.2. EHR Access Control

An EHR system's interoperability allows for large amounts of data storage. Most of the developing world's healthcare has progressed to the point where patients are treated by doctors, therapists, primary care providers (Jin et al. 2009). HIPAA (Health Insurance Portability and Accountability Act) access to patient data in applications is subject to regulatory restrictions (Helms and Williams 2011). Under the HIPAA rules, we are required to implement "mechanisms that record and analyze activity in electronic health information systems" (King, Smith, and Williams 2012). Many access control models are undergrowth to make contact with this legal requirement: Role-Based Access Control (RBAC), Mandatory Access Control (MAC), Usage Control (UCON), Tees Confidential Model (TCM), and Digital Right Management (DRM). When compared to all of the different access control models, UCON is promising. The latest model of access control. A UCON-based system is more difficult to operate than the others. A framework like this takes more resources and time to design and execute. An RBAC model is easier to create than the UCON model. EHR system offers state-of-of security and provides considerable flexibility. Using the (RBAC) approach was found to be appropriate since functions are given permissions (Mchumo and Chi 2010). The people are divided into two groups in the hospital: patients and medical practitioners.

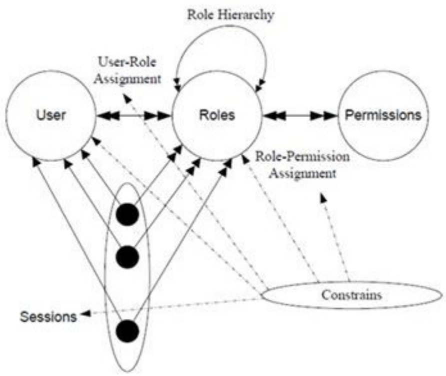

Figure 1. Role-Based Access Control Model (Lu et al. 2017)

3. Design and Implementatıon of E-Health Portal

This section includes the design and implementation of an electronic health portal to deal with patients and monitor Coronavirus cases through reports that are exchanged among doctors and officials. It also allows the patient to access his electronic health record and communicate with the private doctor, know his prescriptions and responses from the doctor, and determine the dates of electronic reservation. This portal was built using several descriptive languages, programming languages, and a database such as PHP, MySQL, HTML, CSS, with Bootstrap framework to make this portal suitable through mobile phones tablets.

The system also includes:

a. Communicating with the doctor by the administration,

b. Identifying emergency cases and outbreaks of serious diseases such as Coronavirus and HIV

c. Sending reports on urgent cases.

3. 1. System Design and Implementation

The user appears in front of three logging options as shown in Figure 2 administrator, doctor, and patient. The interface contains the electronic health portal's name and some details about the institution (such as the name of the institution, private phone numbers, and the location). Access to any of these sections is through a username and password that the portal administrator creates.

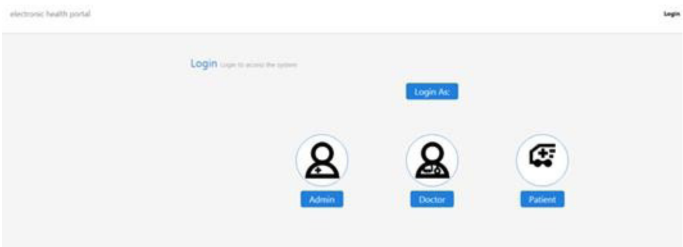

Figure 2. *First page of ehp*

3. 1. 1. Foreground

In this section, the patient and the doctor can access the electronic health portal by registering with the user name and password. Each user, doctor, or system administrator enters the section designated for him/her, as shown by the Figure 3.

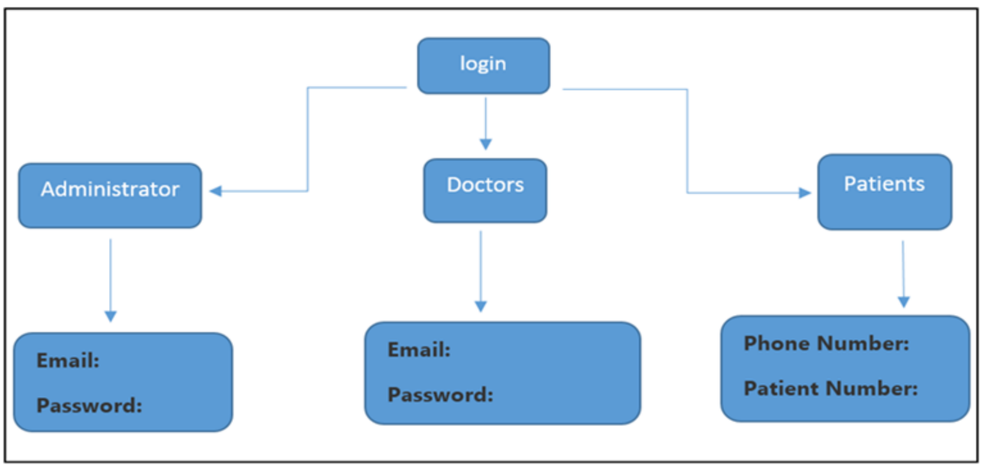

Figure 3. *Foreground Structure*

3. 1. 2. Access control

i. Patients: The login to patient interface by a username (the mobile number is used for ease of use instead of the email because some patients may have no email). The password is given to the patient by the health institution. As is evident, the password is the essential thing that preserves the electronic health portal's security. In this portal, an equation was adopted by the PHP language to maintain confidentiality.

```
$patientNumber = substr(preg_replace("#[^09]#", "", md5(uniqid().time())), 0, 4);
```

The main parts of the code are defined as follow:

a. $patientNumber = A variable representing the patient's number, which is the password in the portal.

b. The substr() function: returns part of a string.

c. The preg_replace() function: All matches of a pattern or list of patterns contained in the input are replaced with substrings, resulting in a string or sequence of strings.

d. The md5() function calculates a string's MD5 hash. The MD5 Message-Digest Algorithm is used by the md5() function from RSA Data Security, Inc.

e. Based on the micro time, the uniqid () function generates a unique ID (the current time in microseconds). The return value's uniqueness is not guaranteed by the provided ID from this function.

The md5() function is used to generate an ID that is incredibly difficult. The time () function comes back to the current time in the number of seconds in the Unix Epoch. This means that the first function substr() will take a part of the string starting from the value 0 by four elements. This is done by replacing the values with the preg_replace () function from the uniqid () + Time () functions, which will be entered into the md5 () function. So that the last function will be a combination of unique ID based on both the micro time and current time in the number of seconds since the Unix Epoch is adopted. Then, md5 () uses the RSA Data Security for the values contained within it. The following simple symbols "# [^ 0-9] #" refers to purifying the resulting series of functions from any symbol or letter and keeping the numbers only so that only the first four digits are taken, thus the patient's password. When registering, the patient cannot see the records of other patients, and medical records cannot be deleted, added or modified, because they are provided by doctors only.

ii. Doctors: Logging in for doctors to the electronic health portal is through an email and password.

This is done through a prior addition by the system administrator. The doctor's password is "hospital", then the doctor can change it from the doctor's department special settings. The doctor can access the patients' electronic health records by knowing the patient's number and approve electronic reservations, add patients to the portal, and add their information and prescriptions in addition to responding to patients' questions.

iii. Administrator: The administrator is responsible for the electronic health portal, he/she works on adding doctors to the portal and following up on updating records, and sending reports on epidemics and online patient reservations.

3. 2. System Functions

In this portal, the jobs are divided into three sections: Patients, Doctors, and Portal Administrator.

3. 2. 1. Patient's functions

When the patient logs into the electronic health portal through the phone number and password previously set by the system administrator, five options for the patient will appear as shown in the Figure 4.

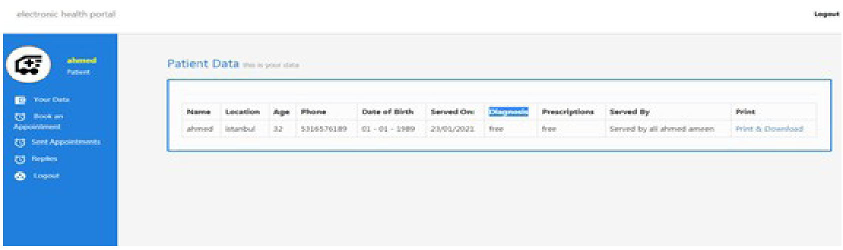

***Figure 4**. patient block diagrams*

3. 2. 2. Doctor's functions

The doctor function includes a dashboard, profile, appointment booking, adding or searching for a patient, patient reservation responses, and adding an outbreak situation such as Coronavirus and HIV reports. The doctor can change his password by modifying the personal information in the control panel. The default password is "hospital".

3. 2. 3. Administrator function

This section, responsible for the electronic health portal, has the advantage of specializing in the database, adding the doctor to the system and delete, following up on epidemiological cases, disease outbreaks, numbers of patients, reservations for doctors, and other features.

3. 3. Test and Evaluation

In this part, many tests are performed to evaluate this system and show how the system meets users' requirements.

3. 3. 1. Add patient

In Figure 5, if the doctor wants to add a new patient, he/she must enter all the required information in the electronic health portal.

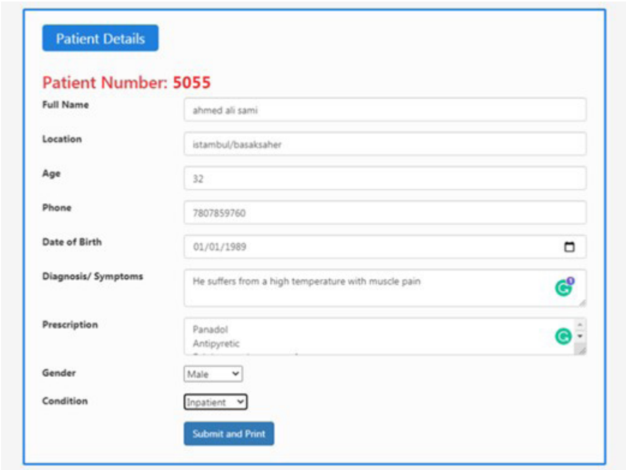

__Figure 5.__ Add patient

3. 3. 2. Patient's booking

In Figure 6, The doctor's window displays appointment bookings and health records. The doctor will access the patient's health record without making any changes through it.

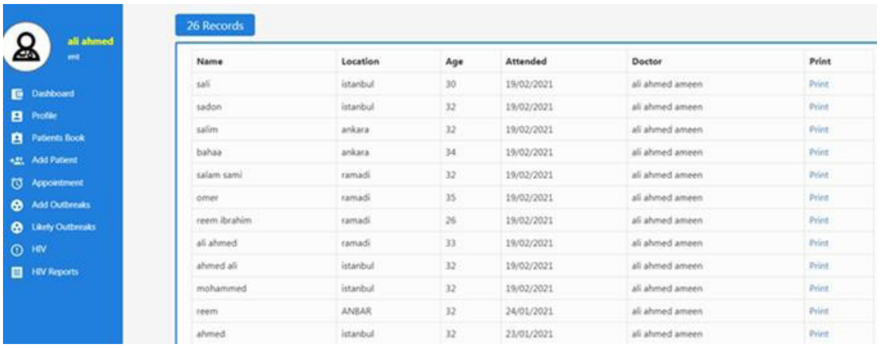

__Figure 6.__ Patients booking

3. 3. 3. Add outbreak

An important addition to our work is this option. The doctor can add a report on a specific patient's epidemiological situation or a new virus outbreak. This report informs the official responsible for the electronic health portal and all the doctors inside the portal about the new situation, see Figure 7.

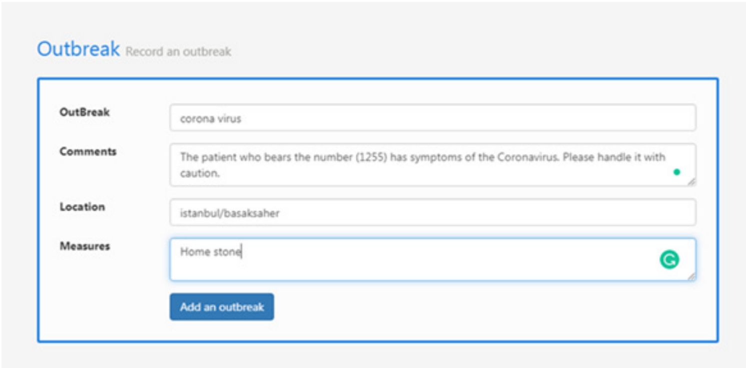

Figure 7. *Add outbreak*

3. 3. 4. Replies of doctor

Figure 8 shows the responses and correspondence between the doctor and the patients. To take an appointment for review and examination or prescribe medication.

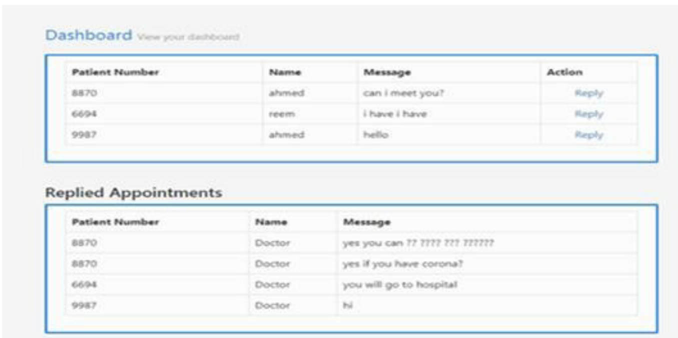

Figure 8. *replies of doctor*

3. 3. 5. Black box test

The black box test is mainly used to test system functionality. It can find the error function, input error, initialization error, and end error. Both input and output scenarios should be included in the overall black box evaluation. As a result, a large number of scenarios must be put to the test in a real-world environment. It is challenging to complete the black box test. As a result, we conducted a series of focused experiments. The emphasis of these tests is on the system's primary role.

a. Function Test

The basic electronic health portal functions are selected as in Table 1.

Table 1. Function Test Result

No.	Function	Expected outcome	Result
1	Add patient	User can login the system.	Pass
2	Add doctor	User can login the system.	Pass
3	password Change of doctor.	A successful notice popup.	Pass
4	Replies.	Doctor can see it.	Pass
5	Book an appointment.	A successful notice popup.	Pass
6	Add outbreak.	A successful notice popup.	Pass
7	Edit& delete.	admin can delete or modify the doctor's file.	Pass
8	create random password for patient.	Generate a random patient password.	pass

B. Submit Data Without Meeting All Field Tests

In this section, we examine not to fill in text areas. There should be a warning popup if the user has not filled all areas of the text to be filled.

Table 2. Non-fulfilled Test Result

	Text field	Expected change	Results

1	Password change	A reminder should popup.	pass
2	Add user	A reminder should popup.	pass
3	Login	A reminder should popup.	Pass
4	Patient details	A reminder should popup.	Pass
5	Add outbreak	A reminder should popup.	pass
6	Book an appointment	A reminder should popup.	pass

4. Results

In the electronic health portal, the access control feature is combined with the application of information sharing. Patients can define the accessibility function using the RBAC model. The doctor cannot modify or delete the patient's file without permission from the patient or the system administrator. It also cannot share patient files to maintain privacy. Therefore, the amendment to the patient data cannot be accessed and modified by the doctor except with the electronic health portal person. Therefore, the patient chooses the doctor who wants to communicate with him/her and add data and prescriptions. In this case, the doctor can view the patient's data and share his data. The patient can communicate with the doctor and receive responses. He can also view and print his health record and prescriptions. Its stock remains in its file. Also, in this electronic health portal, a private password for the patient was created, based on programmatic functions, to maintain the patient's data privacy and security. Using the unique programming functions to create a password based on the RSA algorithm, it becomes clear that the patient's password will be strong and not similar to other passwords, which gives him data privacy and high security.

5. Conclusıon and Future Work

Many electronic health systems fail to meet the requirements to keep the patient's health record electronically, and the patient accesses his health record at any time. Moreover, communicate with the doctor remotely, especially in health institutions that do not have electronic systems to deal with the health record, making the loss of health data a possibility. In this work, an electronic health portal was developed to integrate various medical services and applications. It keeps the patient's privacy and facilitates the patient's communication with the doctor, especially at a time of epidemics. A medical consultation service is also available on this portal, and the doctor sends reports on Coronavirus. In future work, we will work to make the electronic health portal work as an application on mobile phones and websites. Additionally, attaching files and adding more multimedia data to patient's records will be available. Moreover, electronic storage and video chat between the patient and the doctor, which can facilitate the telemedicine process, will be the upcoming feature of the portal.

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RESEARCH ARTICLE

DETECTION OF COVID-19 PNEUMONIA EFFECTS IN CHEST X-RAYS USING DEEPLEARNING

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Abstract: The development of technological tools based on artificial intelligence (AI) could contribute significantly in the fight against COVID-19. AI is the ability of a machine to apply human cognitive functions. In this paper we propose a deep learning based model for COVID-19 detection relying on the effects it yields on the lungs.

Keywords: MRI, XRAYS, COVID-19, Deep learning, svm

1. Introduction

More than one million persons have pneumonia hospitalization, and over 50, 000 die of pneumonia every year in the USA alone (Koo et. al., 2018). Presently, chest x-rays or films are the best way to diagnose pneumonia (Hansell et. al., 2008) and serve an essential role in clinical and epidemiological treatment.. However, detecting pneumonia on radiographs is a difficult task that depends on the availability of radiologist specialists, so there is a wide opportunity to help specialists with new Artificial Intelligence technologies to facilitate their work and improve the health system. As mentioned above, chest film is used in the screening and diagnosis of many diseases of the lungs. A large number of radiograph studies and radiological reports are typically stored in the PACS (Image Archiving and Communication System) systems of hospitals. A good deal of research has been done to take advantage of the knowledge contained in these databases, but there is a very specific challenge: medical records are often loosely labeled and do not contain annotations. This means that the x-ray is associated withthe diagnosis of the specialist doctor -as negative (healthy patient) or positive (identifying the disease). But the radiograph does not contain delimited the region of the image that led him to such a conclusion or diagnosis. So recent research has focused on exploiting these data sets with deep learning paradigms, which require large amounts of data or images, building large-scale CAD systems for medical purposes. Detecting chest diseases and especially pneumonia on x-rays can be difficult for the specialist.

2. Materials
2.1. COVID-19

Currently, the globe is experiencing the um novo coronavirus pandemic, the serious acute coronavirus syndrome 2 or the SARS-CoV-2, known as COVID-19having its first reported case in Wuhan, China, not the end of the year of 2019. Due to its rapid dissemination, it has become a serious problem of public health in the world. In order to diagnose COVID-19, or test that is being used, but due to its lack in some locations and a delay in obtaining the results, it becomes necessary to identify and develop ferments that can help you professionals A number of alternatives to aid in the identification of COVID-19 and the use of chest radiography, which shows characteristics similar to other pneumonia caused by other coronaviruses In the meantime, a rapid radiological interpretation of images is always available, particularly where we have few resources that pneumonia (caused by viruses and bacteria) has a higher incidence and higher mortality rates. The process of interpreting agents (brain tumors or lung anomalies, for example) is a complex activity and, therefore, is necessary, or the use of image processing techniques, often combined with machine learning techniques, to identify applications of deep learning techniques (deep learning) to classify images of x-ray images and a considerable growth in recent years. Several investigations address this topic, such as performing the classification of images to help prevent early diagnosis of tuberculosis, and classifying injuries through chest radiography also used for classifying x-ray images of the x-ray with pneumonia and other injuries.

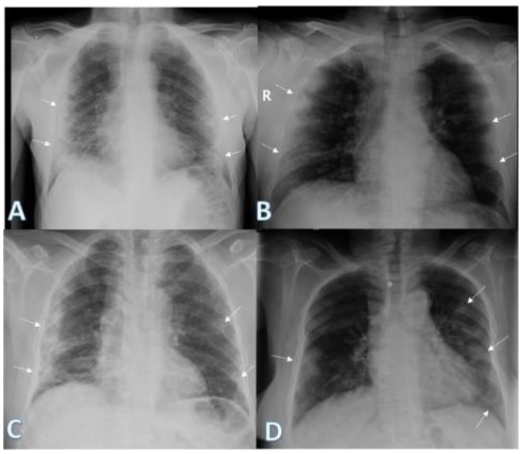

Figure 1. *Effect of COVID19 in Xrays*

2.2 Deep Learning

The deep learning paradigm is a sub-area of machine learning that addresses or automated learning, being carried out through the use of successive deep layers within a neural network architecture. Asa result, each litter passes or the result of its learning for the next litter. The greater the quantity of litters, the deeper the neural network becomes. A main characteristic of deep learning is the use of litters to perform the extraction of characteristics and classification of two dice. As a result, deep learning algorithms have become viable options for image classification tasks, for example.

Deep Learning is a machine learning approach, a branch of artificial intelligence, allowing computers to resolve issues that they would otherwise be impossible to solve. Although a systematic method to deep networking was available since the 1980s, it could not be expanded into large networks and research from neural networks entered a spell of slumber. Hinton GE et al. (Ooi et. al., 2004) showed that deep neural networks could be efficiently trained using a state-of-the-art result of handwritten MNIST digit data set from 2006.

3. Proposed Method

The methodology provided here is a multiple classification issue, as the X-ray picture is identified and classified in 8 potential groups or disorders. We use the ChestX-ray8 data and train it using a convolutionary network to do the ranking and get a model after a number of subtle changes, such as weight loss or weight elimination and L2 regularization, among others. One of the main issues with learning when dealing with data sets, such as those employed in this research, is training. Data increase (A.D.), which generates extra training information from existing samples, is a commonly used approach. Apply a variety of random changes that yield plausible visuals to these samples. The data enhancements procedure may dramatically minimize validation loss, in which both identical convolutionary networks display the graph with training and validation data, one without data enhance and the other with this method. Data increase clearly addresses the overtraining issue on the left side of the picture, in which it is noted that the value of the loss function lowers with validation data first and then grows again. While the training data continues to diminish. The right side of the picture depicts, amongst other ways, how validation loss may be regularized by adding data. There are two dual-head cameras and both per- and inter-critical exams are taken on the same camera.).

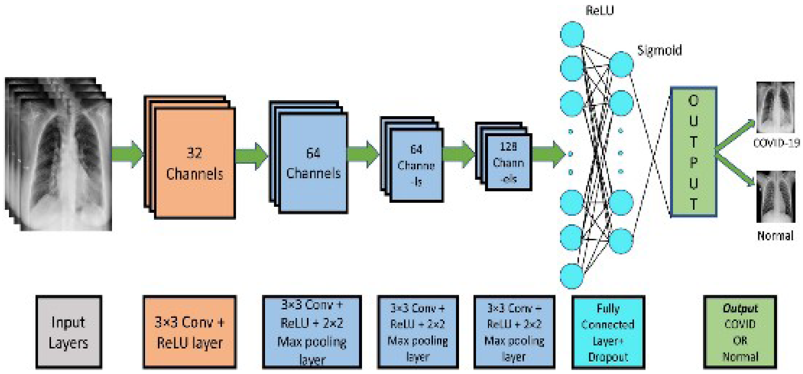

Figure 2. *CNN architecture*

As we shall see in the following section, however, if data enhancement procedures are performed without respect to picture quality, some bad training examples may lead to a less than optimum model of the convolutionary network. In several computer vision applications, the data increase strategy has shown to be an effective strategy; nevertheless, as we see in the next section, some crucial considerations are taken when applying this procedure to medical imaging. The difficulty occurs because certain photos in the data collection are poorly quality, which might influence the training and create a sub-optimal model. These models may create a huge number of false positive or worse ones, as the authors extensively demonstrate in (Ajlan et. al., 2014), and misclassify a new test sample. Theauthors of this research used a battery of testing, in which they assessed the performance of certain famous networks such as VGG16 and GoogLeNet utilizing imagery changed with several sorts of aberrations in picture quality: compression, poor contrast, blurry and Gaussian noise. The scientists observed that the networks are compression-resistant, but are heavily influenced by the other three.This has led to a lot of study in this field, with some studies focusing on the implications these distortions have on the quality of picture for various computer vision tasks based on deep learning networks (Kanne, 2020). This is particularly important for medical imaging, especially with ChestX-ray8, which includes 108,948 frontal radiographs of 32,717 unique patients, collected between 1992 and 2015, with eight common diseases obtained by the use of natural language processing techniques for the mining of radiological reports. As far as we know, no assessment has been carried out in prior studiesusing this data set, including a high number of low quality photos, as seen in Figure 4, which is presumably introduced by the method the authors produced the data set. Some of the photographs have very little contrast, while others are not focused or lack clarity, others are very saturated. The second contribution in this paper is to do an image quality evaluation in addition to the above mentioned data increase technique to decide if the example training may be deemed a suitable candidate for the data enlargement phase and beyond. Training phase processing. Some issues for the assessment of picture quality and the methods used to evaluate it.

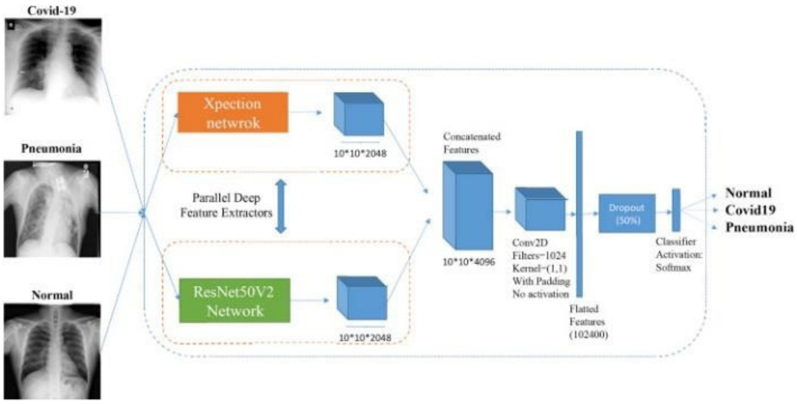

Figure 3. *Proposed Network detection*

As previously indicated, the quality of the input pictures may greatly impair the performance of convolutive network models; the authors of (Ajlan et. al., 2014) undertook tests of Gaussian noise, blur, compression and poor contrast. Even for minor degrees of noise or blur, network accuracy reduces dramatically, and the combination of multiple of these visual defects can only yield worse results. Thus, in this paper, we are implementing a 'filter' or selection process based on several classic image processing metrics1, in order that an image may or may not be considered for post-processing, such the SNR., the black index and the image variance to determine the contrast. These metrics are often correlated: A high noise picture has poor contrast and excessive blurring.

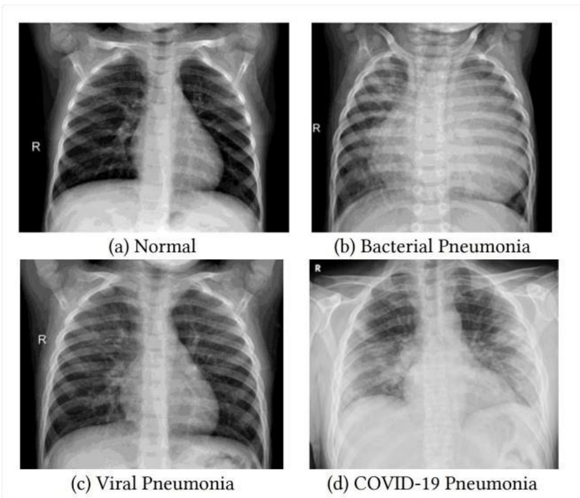

Figure 4. *Input images for training the model*

4. Results

To evaluate the results, the metrics of Accuracy, Precision, Revocation, F1-score and confusion matrix were used. The confusion matrix is generally used in machine learning, having information about the real and predicted classifications performed by a classifier In a confusion matrix the lines are real values in each class, while the columns are the predictions made by the model. The values obtained from the confusion matrix are also used to generate some extremely important metrics for the evaluation of the models, such as: Accuracy, Precision, Revocation and F1-score These metrics are commonly used in the evaluation of learning models From the results obtained, it is possible to see in Figure 3 the performance of the generated models, in the training and test stages. The analysis parameter used was the accuracy per season, that is, the success rate in each season. Proposed CNN-SVM achieved a faster convergence than InceptionResNetV2, both in the training stage and in the test. It is worth noting that there was a discrepancy between the curves in the test stage, which shows that the Proposed CNN-SVM achieved a better performance.

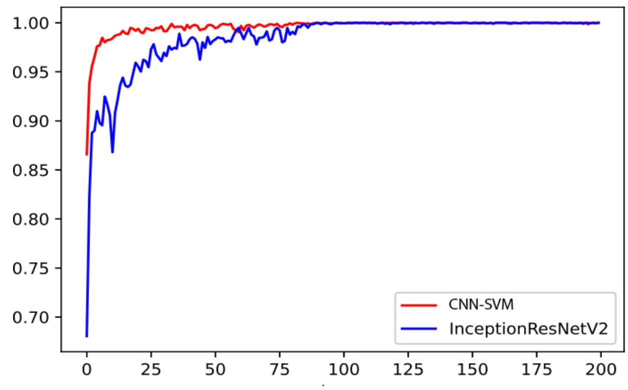

Figure 5. *CNN-SVM vs RESnet Accuracy*

In figure 4.8 it is possible to see the results of precision, recall and f1-score for each class for each architecture. For all classes and metrics, the Proposed CNN-SVM achieved the best result. With this, the Proposed CNN-SVM model is able to not confuse the classes (precision) and is able to find the largest possible number of images of each class (recall). The f1 score is the weighted average of the two metrics:

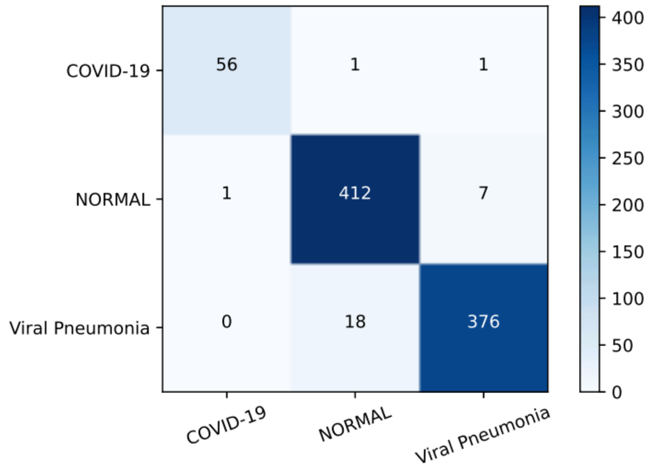

Figure 6. *F1 score of the CNN-SVM detection*

5. Conclusion

Based on the results achieved, we can observe that the model generated through the Proposed CNN-SVM architecture obtained the best performance in the diagnosis of COVID-19, the focus of this study. In all the metrics analyzed, Proposed CNN-SVM obtained a result superior to InceptionResNetV2. Because it achieves a higher hit rate (accuracy) than InceptionResNetV2, Proposed CNN-SVM becomes a feasible choice of architecture to be further explored in future works.It is important to emphasize that this study has as its premise to serve in the future as an alternative way of screening patients. From this study, new possibilities can be explored. A WEB system can be developed in order to serve as a test environment for the model that was trained, that is, the user will be able to upload an x-ray image of the chest of a patient with suspected COVID-19 and the model will generate a possible pre-diagnosis of the image. As a way to optimize and improve the previous proposal, it will be necessary to use more databases containing images of patients diagnosed with COVID-19 or other diseases that can be diagnosed through x-ray images, to enhance and generalize the model.

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RESEARCH ARTICLE

DETECTION OF COVID-19 IN LOW ENERGY CHEST X-RAYS USING FAST R-CNN

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Abstract: In recent years, it has been shown that deep learning can produce similar performance increases in the domain of medical image analysis for object detection and segmentation tasks. Notable recent work includes important medical applications, for example, in the field of pulmonology (classification of lung diseases and detection of pulmonary nodules on CT images in this paper, we present a variation of CNNs, which works extremely well on a current data set — a customized architecture with optimal parameters. In our contribution, we focus on lowering the complexity of our network, while yet reaching a phenomenally high degree of accuracy. To achieve this aim, our model has been tailored for high performance and an easy design.

Keywords: component, formatting, style, styling, insert

1. Introduction

Radiology offers a crucial benefit when we monitor the way the illness progresses, and because of its availability it is a frequent approach (Song et al. 2020) (Shuja et al. 2020). In addition to biological procedures, the study of lung rays – such polymerase chain reaction (PCR), which permits the identification of infectious disorders – might therefore be immensely valuable particularly for nations with limited access to biomedical facilities. Given the successful use of deep learning architectures (DL architectures) in several areas, including medical image processing, this might boost our capacity to handle the difficulties of identifying the disease (Tartaglione et al. 2020).
In reality, the capacity and effect of these cutting-edge procedures are continually growing (Shi et al.

2020) (Karim et al.2020). Many academics now have an interest in the creation of deep neural networks (R-CNNs), which can accurately (and concurrently rapidly) identify COVID-19 symptoms (Victor et al.2020). A number of research have shown that R-CNNs, in particular convolutionary neural networks (CNNs), (Selvan et al.2020) recognize the symptoms of COVID19 in radiation (Alafif, 2020) effectively.

A number of recent research have been carried out employing Computer Tomography (CT) scans or X-rays to do a comparative analysis of pre-trained DL models used to grade COVID-19 in particular datasets (Khan et al. 2020), (He et al. 2016). However, the state-of-the-art research contributions mainly include 'transference learning' (Simonyan & Zisserman 2015) (Huang et al. 2017) as the automated identification strategy for COVID-19 symptoms. These contributions aim to establish new ways, although they have their own problems.

In general, the fundamental concern in regard to these methodologies is that the accuracy of these constructed models improves only at the expense of great complexity. In other words, considerable precision is gained, given the complexity of the systems increases.

2. Materials and Methods

2. 1. Covid-19

Coronaviruses are a broad family of viruses that may cause animals or people to get ill. Seven coronaviruses may cause infection in humans all around the globe, however these four human coronaviruses are usually infected: 229E, NL63, OC43 and HKU1. Air infections normally range from simple cold illnesses to more serious illnesses, such Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory syndrome (SARS) and infectious disorders caused lately by the coronavirus (COVID-19). (Goodfellow et al. 2017) This zoonotic sickness caused by severe acute coronavirus syndrome 2 (SARS-CoV-2). This infectious condition was previously designated New Coronavirus-Infected Pneumonia (NCIP) by WHO and was recognized a new coronavirus in 2019. (2019-nCoV). On 11 Feb 2020, the (WHO) formally renamed the COVID-19 (Corona Virus Disease-19) clinical condition reported in a tweet. In Wuhan, Hubei Province in China, the epidemic of COVID-19 caused by the 2019 new coronavirus (SARS-CoV-2) started in December 2019, and the current epidemic was an official pandemic. (Ai et al. 2020) As understanding about the virus has evolved fast, readers are recommended to continually update themselves (Fig. 1).

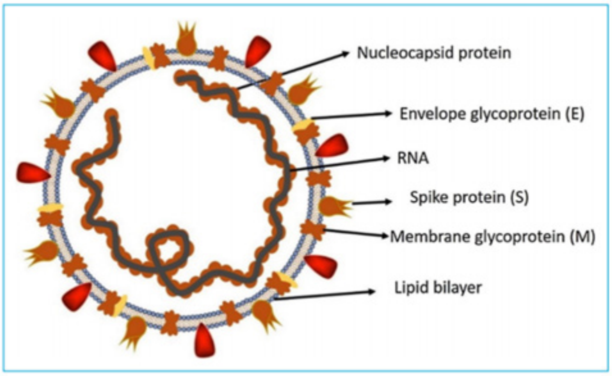

Figure 1. *Covid-19 structure*

2.2. Fast R-CNN

The architectural selection utilized is based on the excellent results achieved with CNNs in the latest image classification projects of COVID-19 and excellent results in other comparable tasks with this kind of architecture (Selvan et al.2020), (Alafif, 2020), (Khan et al. 2020). We have adopted a single shot multibox detector network design as presented in (El Asnaoui et al. 2020) (SSD).

This design is designed for items detected by a single deep neural network in photos. This strategy discrete the bounding box output space into a series of default boxes spanning various aspect ratios and sizes by position of the characteristic map.

The network provides scores for the presence of each object category in every default box at the time of prediction and makes tweaks to the box to better fit the object form. The network also mixes predictions from numerous maps with varying resolutions to handle objects of diverse sizes organically. Experimental findings on many outstanding datasets demonstrate that SSD is equivalent to approaches that leverage more than one architecture for objects to be detected considerably quicker, while offering a unified training and inference framework.

In comparison with previous single-stage approaches, even with a lower input picture size (El Asnaoui et al. 2020), SSD is much more accurate. In this design, we employ VGG-16 (Vaid et al. 2020) as the basis network for extracting functions. This model is based on Fast R-CNN, too. We have various boxes with varied sizes and varying aspect ratios across the complete picture during training. SSD detects the box with more IOU compared to the reality of the ground.

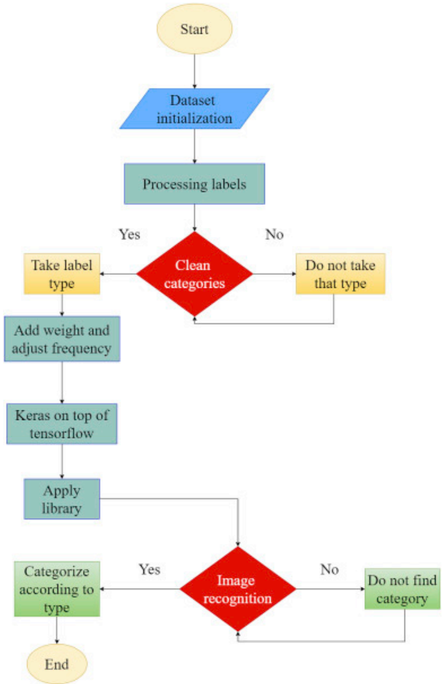

Figure 2. *Fast R-CNN for Dataset Labelling.*

3. Proposed Method

In this work we train a variation of R-CNN called ResNet-50 CNN, with the ImageNet database conventional transfer learning algorithm, was employed. The validation accuracy of these networks has not surpassed 98% and some of them show a very low level of precision. In addition, ResNet-50 is used as the extractor of features and SVM as the classification in (Luz et al. 2020). This work is not a complete network and the low number of COVID-19 X-rays on the data set (25 pictures) does not provide the result that much value. With ResNet-18 modified, (Das et al. 2020) produces a deep convolutionary generative opposing network for synthetic data, but cannot create unusual synthetic data since a proposed network is independently trained for each class. The test accuracy for COVID-19 detection is 82.91 percent, the deep revolutionary auto-encoder methodology, is suggested by (Maguolo & Nanni 2021). After 3 times cross-validation, for the binary classification, a pooled ROC–AUC of 0.6902 is achieved. The Residual Neural Network (ResNet) model is an upgraded neural network version (CNN). ResNet offers shortcuts to address an issue across layers. This avoids distortion, as the network deepens and becomes more complicated. Bottleneck blocks are also utilized to speed up training in the ResNet (Hammoudi et al. 2020) model. ResNet50 is a 50-layer ImageNet dataset trained network. ImageNet is an image library with over 14 million photos from over 20,000 categories designed to compete for image recognition InceptionV3 is a kind of neural network model. It comprises multiple phases of convergence and maximum pooling. It includes a fully connected neural network in the final phase (Islam et al. 2020). As with the ResNet50 paradigm, ImageNet trains the network. The model comprises of a profound convolutionary network with the architecture Inception-ResNetV2, which was trained on the dataset ImageNet-2012. The input is a 299 to 299 picture and the output is a list of class probabilities computed. ResNet101 and ResNet152 are composed of 101 and 152 layers owing to the blocks of ResNet layered. A trained version of the network may be loaded from the ImageNet database on over one million images (Waheed et al. 2020). The network has therefore learnt a rich depiction of a variety of pictures. The network has a 224x224 picture input size.

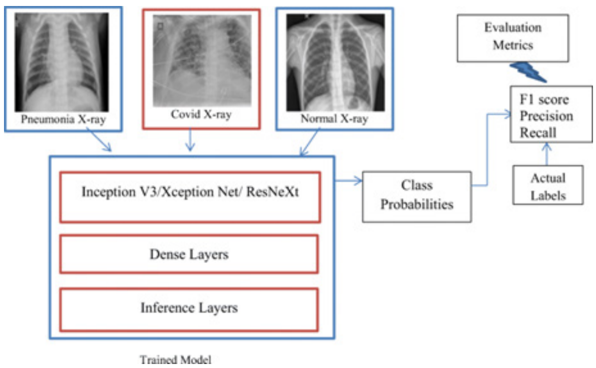

Figure 3. *Inception, RESNET, Fast R-CNN Training on the Proposed Dataset.*

3 distinct binary classifications were carried out with 4 distinct classes (COVID-19, normal, viral pneumonia and bacterial pneumonia). The approach of 5-fold cross validation was utilized to get robust results using 5 separate, pre-trained models, InceptionV3, ResNet50, ResNet101, ResNet152 and Inception-ResNetV2 in this work. Although 80% of the data is allocated for training, the remaining 20% is for testing. This same procedure has proceeded till every 20% component has been evaluated. Figures 4 and 5 first of all, the accuracy and loss values in training process for Dataset-1 models including binary class-1 (COVID-19/normal classes). It is obvious that the ResNet50 model performs better than the other models. It is possible to say that the ResNet50 model obtains lower values between other models' losses. Figure 6 shows the detection performance of test data. Although there are many oscillations in certain models, some models are more stable. After the 15th epoch, the ResNet50 model seems to have less oscillation. Table 2 provides comprehensive performance numbers for each model fold value. The detection of the ResNet50 model in class COVID-19 is shown in Table 2 to be much higher than other models. The greatest overall performance is ResNet50 and ResNet101 with 96.1%. It is clear that additional normal data leads to improved performance in all models.

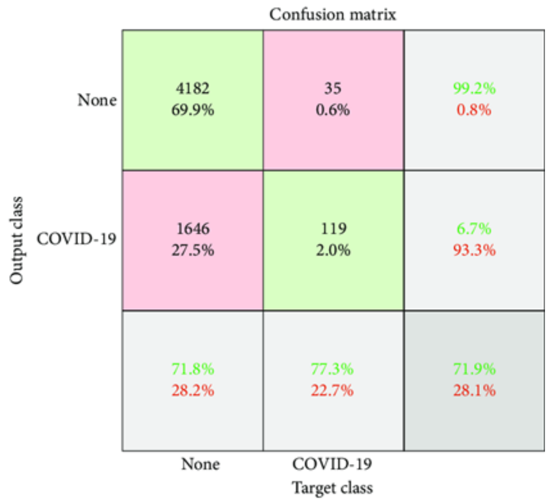

Figure 4. *Covid-19 Detection F1 Score Confusion Matrix.*

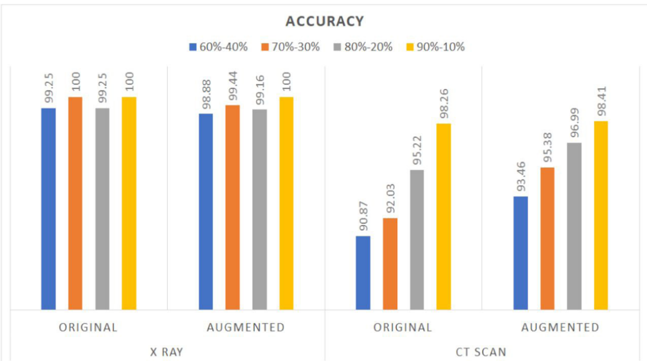

Figure 5. *Accuracy and Error Rate of Each Dataset (CT and X-ray)*

4. Conclusions

A rapid diagnostic approach plays an important role in the fight against infectious illnesses and pandemic conditions such as the present COVID-19. Some drawbacks of the PCR test show that fast alternative approaches are needed in order to serve front-line specialists to make their diagnosis quick and precise. The development of R-CNN-based networks that can quickly and effectively recognize the symptoms of COVID-19 and, at the same time, have straightforward topologies is of considerable significance to researchers.

In this respect we compare remarkable methods to the binary classification of contaminated photos with the use of very accurate deep learning algorithms (a general framework that we called COVID-in-Depth CoDe).

We also suggest a variation of a convolutionary neural network that works exceptionally well with improved parameters on a recent dataset. The model shows an average performance accuracy of 99.90% for 5-fold cross validation, and 99.80% for the single COVID-19 identification. The 99% test accuracy shows that the model is very accurate. Furthermore, we use two external data sets to evaluate the performance of our model, while the results show that the model achieves 92.95% and 85.96% accuracy. The additional success here may be suggested by generalizing the CoDe Framework via the provision of relevant datasets for training the model, which may be sufficiently big and well-balanced.

This study may also be expanded to models that can recognize the phases of COVID19 development as a future effort. As the subject of this research is still in its infancy, we last note that the findings provided might be expanded in several ways. Authors and Affiliations

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RESEARCH ARTICLE

A NEW METHOD BASED CNN COMBINED WITH GENETIC ALGORITHM AND SUPPORT VECTOR MACHINE FOR COVID-19 DETECTION BY ANALYZING X-RAY IMAGES

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Abstract : COVID-19 is an infectious disease caused by the most recently discovered coronavirus. This new type of virus and disease was unknown before the outbreak began in Wuhan, China in December 2019. COVID-19 poses a serious public health threat. Older adults and people with pre-existing medical conditions such as diabetes, hypertension, heart disease, chronic lung diseases, obesity are at higher risk of experiencing complications and serious illness. The computer scientist applied several machine learning and deep learning techniques to detect COVID-19 in last year. In this study, efficient COVID-19 detection framework presented to detect COVID-19 by analyzing x-ray tests. The proposed framework based CNN combined with genetic algorithm and SVM classifier. The main contribution in this study is combining CNN with genetic algorithm and SVM to detect COVID-19 with accurate estimation and minimum execution time. Several scenarios are executed to validated the presented method. Finally, the obtained results compared with several studies presented to solve this problem.

Keywords: COVID-19, Genetic algorithm, SVM, CNN.

1. Introduction

COVID-19 is a serious epidemic disease that emerged in Wuhan, China in December 2019, passed from bats to humans, spread all over the world in a very short time, turned into a pandemic and collapsed the health systems of many countries. Severe acute respiratory syndrome, COVID-19, causes severe respiratory failure in infected organisms with fatal consequences as the disease progresses. The main symptoms and signs of the disease; known as fever, dry cough, sore throat, headache, weakness, weakness, diarrhea, shortness of breath. In more advanced cases, it can progress to severe pneumonia, which causes pneumonia due to oxygen imbalance and multiple organ failure. The disease has much more dangerous and tiring consequences, especially for people with chronic diseases, people with weak endurance and immunity, smokers and the elderly (WHO, 2020), (Chen et al., 2020), (Yin and Wunderink, 2018), (Wang et al., 2020).

COVID-19 is usually transmitted through physical contact eg. B. by respiratory, hand or mucus contact with a person carrying the virus (Diprose et al., 2017). Antibiotics, antimalarials, antipyretics, cough suppressants, and pain relievers are commonly used to treat illness after infection. Hospitalization of infected patients depends on the degree, condition and severity of the disease. The number of patients infected with the COVID-19 virus around the world is increasing day by day. Even powerful countries like the United States, Italy and Spain failed to protect themselves from the virus and were badly affected. With all of this information, given the health system, early diagnosis of the disease is essential to completely prevent a pandemic, or at least to minimize potential damage from the virus. In other words: at least suspected cases must be recognized without error, quickly and accurately (Li et al., 2020).

Currently, the real-time reverse transcription polymerase chain reaction (RT-PCR) is widely used in the diagnosis and diagnosis of COVID-19. Chest x-rays such as computed tomography (CT) and x-rays are preferred for the early detection of COVID-19. The rapid spread of the disease and increasing death rates in many countries point to the need for effective treatments. Therefore, disease management, including diagnosis, early quarantine, and follow-up care, is essential. For now, AI can contribute to the above perspective. Despite strong similarities and a severe shortage of skilled workers between COVID-19 and traditional pneumonia, artificial intelligence (AI) -based self-recognition models may be an important step in significantly reducing testing time There is sex (Li and Zhu, 2020). In this context, artificial intelligence (AI) solutions, effective in solving complex problems, are essential. The solution under study offers both inexpensive and more accurate diagnostic-diagnostic treatment for COVID-19 and similar diseases. Today, especially in the medical field, positive results are obtained with deep learning techniques using imaging data sets such as retinal imaging, chest x-ray and brain MRI with deep learning. It is used in many applications to extract, analyze and recognize data patterns (Huang et al., 2020).

In this study, using the widely used deep learning approaches Convolutional Neural Networks (CNN) technique with new structure and SoftMax method, three different conditions (COVID-19, viral pneumonia, and normal) were used to diagnose COVID-19. The aim of this study is to diagnose and detect patients with COVID-19. In the second part of the study, literature review; In the third part, the details of the method and technique, in the fourth part, the experimental findings and finally in the fifth part, the results and suggestions obtained from the study are given.

2. Convolutional Neural Network Based on Support Vector Machine and Factor Analysis

In this chapter the proposed method of our research named convolutional neural network based on support vector machine and factor analysis was proposed. The proposed method consist from three stages, feature extraction using CNN, genetic algorithm applied as feature selector to reduce the size of output features of the CNN. Then, SVM applied for for classification of the extracted features.

In the first stage, AlexNet is a CNN channel hosted by Alex Krizhevsky. AlexNet was involved in ImageNet's core work on image recognition in 2012. The network was ranked in the top five errors with a 15.3% rate, down 10.8% from its completion rate.

AlexNet is the name of a convolutional network that has had a great impact on machine learning, especially in deep learning computer vision applications. As you know, we won the 2012 ImageNet LSVRC competition by a wide margin (26.2% (second place) with an error rate of 15.3%). Network - Yang LeCun et al. But LeNet was deeper in a convolutional layer that applies multiple filters layer by layer. Consists of 11x11, 5x5.3x3, line, max connection, interrupt, data increase, ReLU trigger, SGD with pulse. Activating Connected ReLU after fully connected layer with all stacking layers. AlexNet trained with two Nvidia Geforce GTX 580 GPUs simultaneously for six days, splitting the network into two channels.

AlexNet has eight levels. The convolutional layer was the first 5 geotags, some of which had the maximum level of clustering, the fc layer shown in the last three, and the activation function was not applied. Shown improved training accuracy for Thane and Sigmoid. The AlexNet structure presented in the Figure 1.

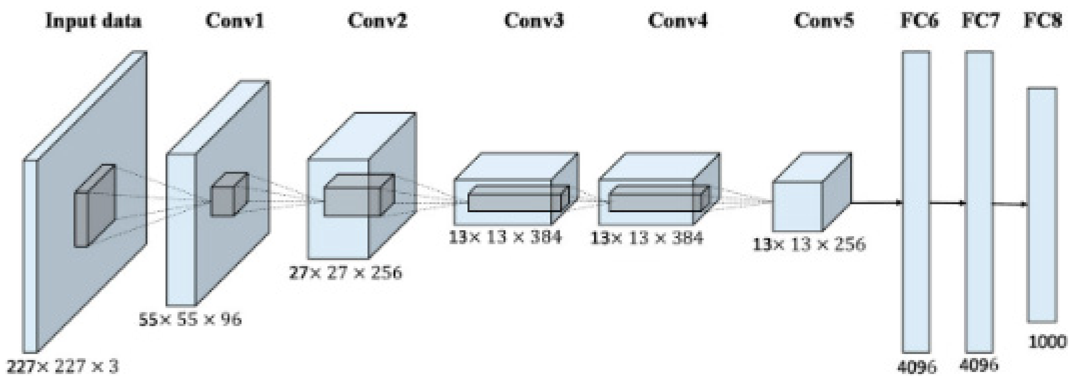

Figure 1: *AlexNet Structure*

Then, the Genetic Algorithm, used in the field of Artificial Intelligence, is a kind of algorithm that searches for the best spot. It's about finding a solution to a problem. If we can turn real problems (like containers on dry cargo ships, how to move from point to point, how to create optimal delivery routes, etc.) into research problems, we can solve this problem. Genetic algorithm's theme. A genetic algorithm (GA) is a function that performs permutation-based optimization and looks for a criterion for the likelihood of convergence. It is a research and optimization method that works in the same way as the evolutionary process observed in nature. Genetic algorithms are described in the literature as follows: Genetic algorithms are powerful evolutionary strategies based on the basic principles of biological evolution. The researcher must first correctly identify the type of the variable and the problem with which he is dealing, and then code according to that definition. Then the fitness function is determined, which is one of the inputs to the algorithm, and this is the objective function that needs to be optimized. Genetic operators such as mating and mutation are applied stochastically at many stages of evolution, so it is necessary to determine the probability of their occurrence. Finally, we need to meet the convergence criteria and solve the problem at the lowest cost. If the problem is influenced by too many factors, the literature recommends using a genetic algorithm to solve it.. Briefly, the working principle of the Genetic Algorithm is as shown in figure 2.

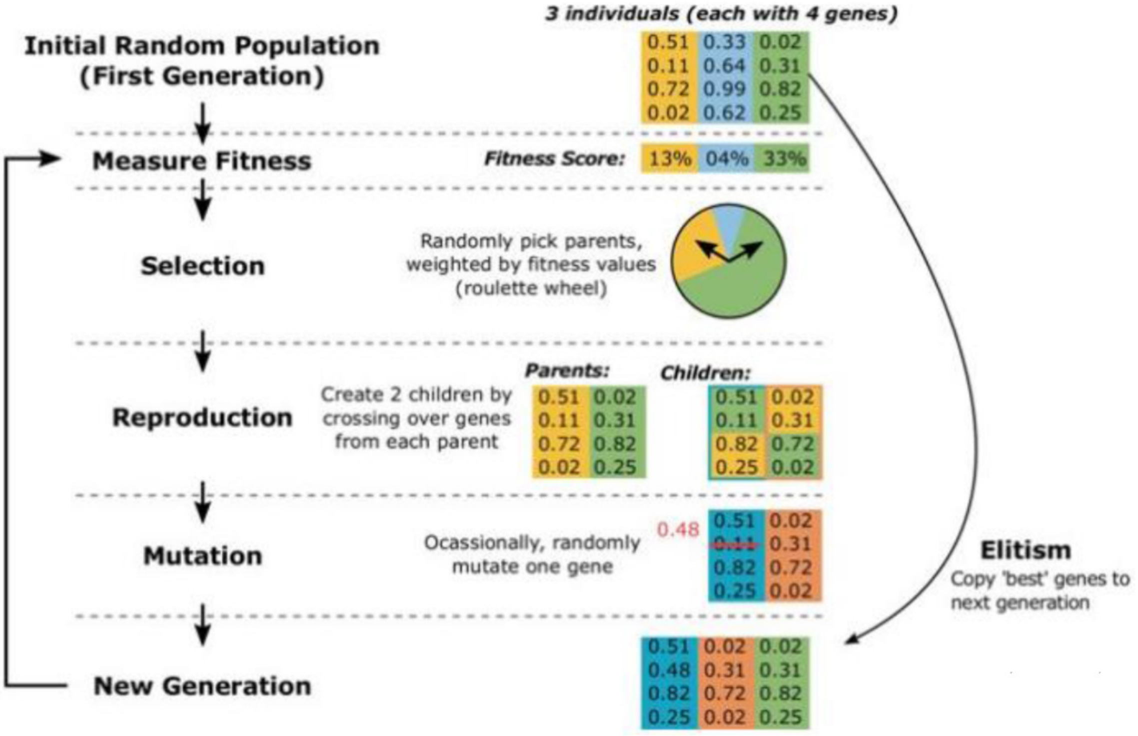

Figure 2: *GA Process.*

The flowchart of the algorithm presented in the figure 3.

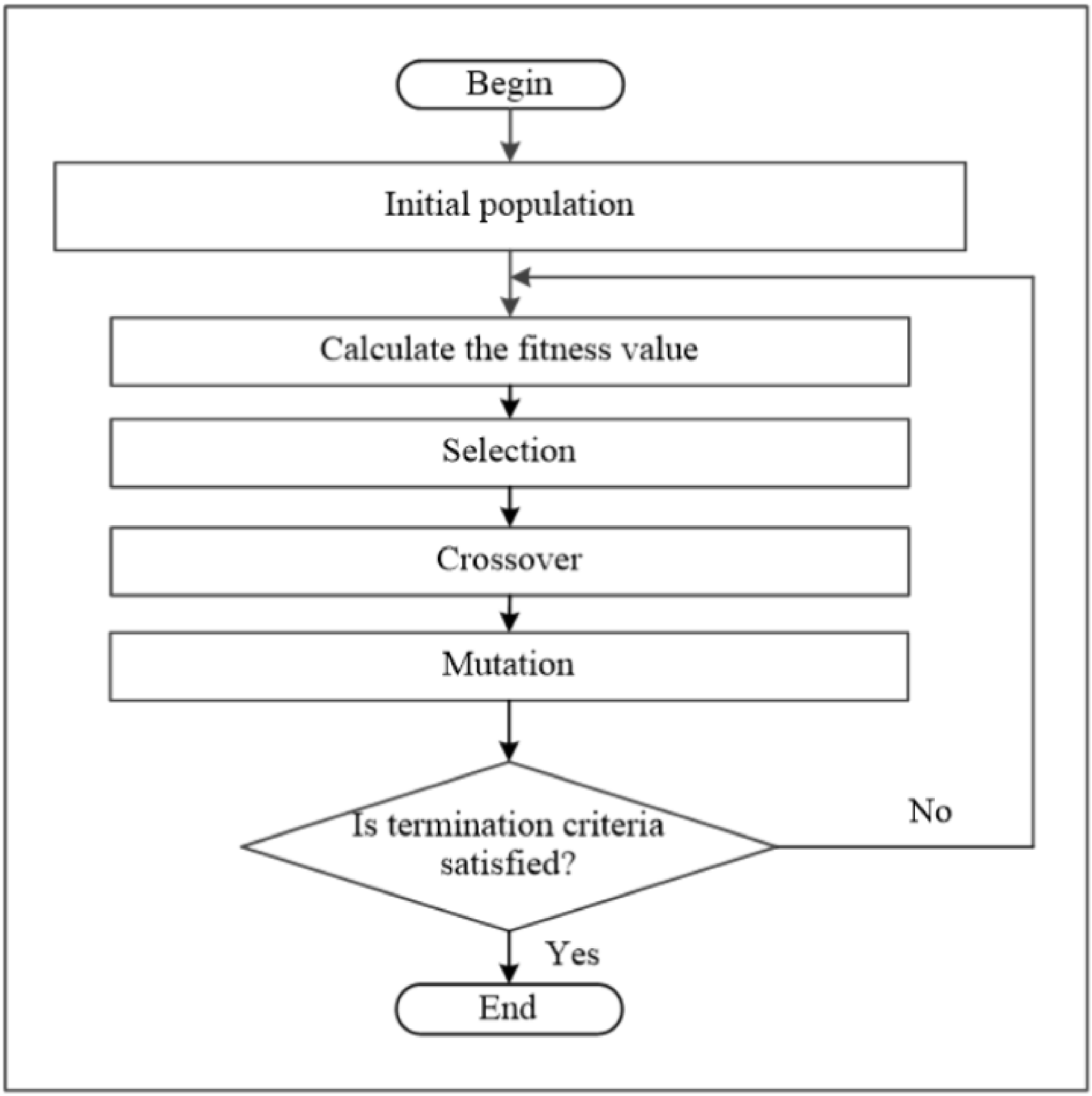

Figure 3: *GA flowchart.*

How people understand a problem depends on the problem. The most important factor that determines the success of the genetic algorithm in solving a problem is the representation of the person who offers the solution to the problem. Everyone in the population has a fitness function to decide whether there is a solution to the problem. Individuals who score higher according to the evaluation obtained by the fitness function are capable of producing offspring with other individuals in the population. At the end of the mating process, these humans give birth to new humans called babies. The child has the characteristics of the parents (mother, father) who created it. Individuals with low fitness scores are less likely to be selected when creating new individuals, so they will be removed from the population after a while. A new population is created by increasing the number of healthy people in the old population. At the same time, this population contains most of the characteristics of well-educated individuals from the previous population. Therefore, good traits are passed down from generation to generation and combined with other good traits as a result of a genetic process. The more individuals with a high fitness value come together and create new individuals, the better a working area is obtained in the search space. In order to find the best solution to the problem; The concepts used in the genetic algorithm are used in a similar sense to the theory of evolution in biology. In natural life, populations are formed by the coexistence of individuals. The population created for the GA algorithm is formed by the gathering of many individuals, in other words, by the gathering of many possible solution candidates. Candidate solutions are kept in sequences coded according to the problem. Each element that makes up this array is called an individual, and each individual represents a specific region in the search space.

In the genetic algorithm, the first starting individuals are usually randomly generated, but this is not a requirement. Especially in very constrained optimization problems, better candidates can be created by paying attention to some of the defined constraints to create the starting individuals. As a result of exposing individuals to the fitness function process, the fitness value, which evaluates how close the solution is to the optimal solution, is determined. The genetic algorithm with the initial population created works with three evolution operators. These; selection, crossover and mutation operators. In general, each of these operators is applied to each individual of the population that will form in the next generation.

Selection is the process of selecting parent individuals to create new individuals based on their fitness values in the population. The crossover operator is applied after the selection process and expresses the mutual replacement of certain parts of the chromosomes of the parent individuals and thus the formation of individuals with new characteristics. The mutation process is the process of changing a gene in any of the chromosomes of the newly formed individual depending on the probability of mutation.

There are various methods to terminate the genetic algorithm process. These methods are; When the desired solution is found during the operation of the algorithm, when the total number of iterations defined at the beginning of the GA is reached, or when the fitness value remains constant, the solution represented by the best individual found is presented as the most suitable solution found for the problem.

In the last stage, the SVM applied to classify the selected features by the genetic algorithm and the flowchart of the method presented in the Figure 4.

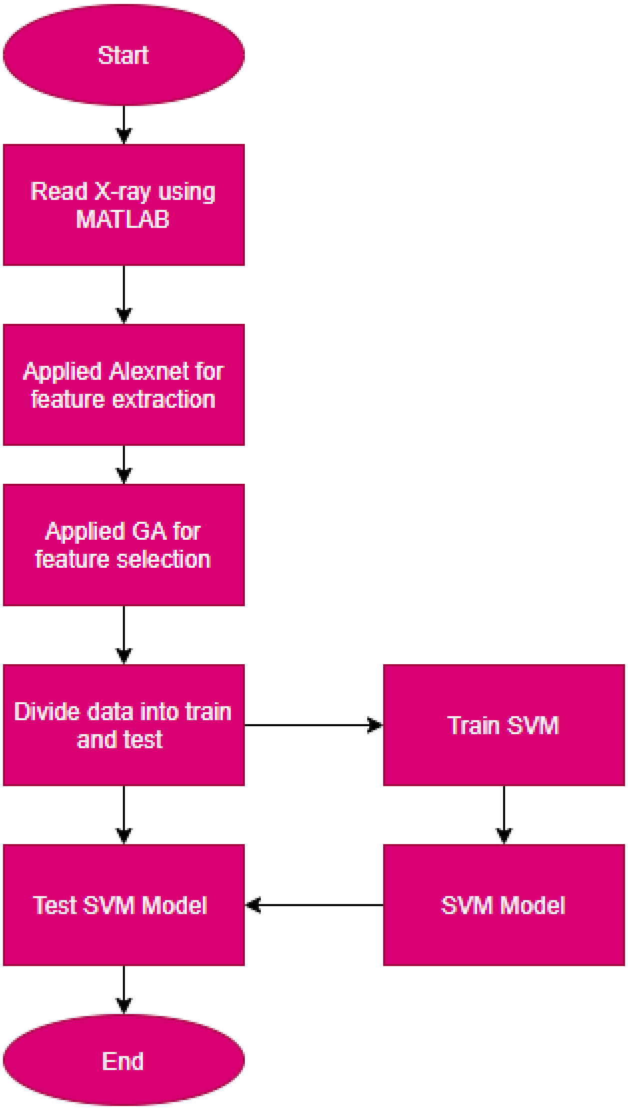

Figure 4: *Proposed Method flowchart.*

3. Experimental Results

In the chapter, the results of the proposed method presented and explained using confusion matrix to evaluate the results. The parameters that are calculated in this chapter lead to diagnosis the power and weaknesses of the proposed method.

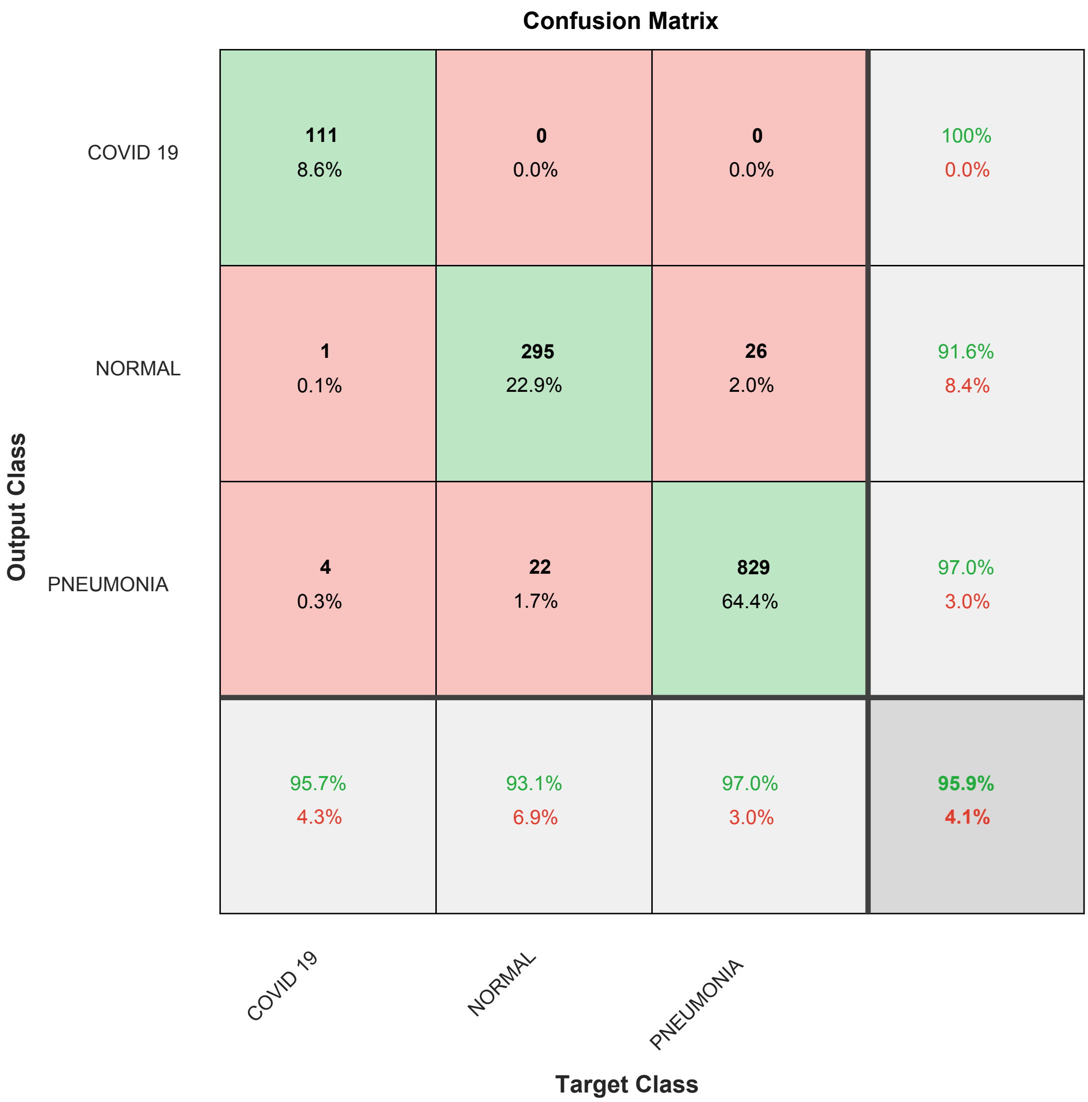

Figure 5: *Confusion matrix of our method.*

The presented framework is also compared with previous studies the proposed in related researches and is shown in Table 1.

Table1: Comparison with litreature

Ref	Acc (%)
Li and Zhu, 2020	92.3
Afshar et al., 2020	88.90
Farooq and Hafeez, 2020	95.7
Chowdhury et al., 2020	96.2
Batık et al., 2018	87.02
Gao et al., 2008	96.6
Karim and Mishra, 2022	96.67
Our Method	99.59

By analysing of the Table 1, the results show that the proposed method presented best results than other state-of- the-art studies. The presented method uses classical methods such as CNN and genetic algorithms, which can show remarkable results with a small number of datasets. On the other hand, deep learning methods require large amounts of data to perform better than other methods. Also, training is very expensive due to complex data models.

4. Conclusion

This thesis has developed a new COVID-19 detection framework that uses a SVM classifier based on CNN models and genetic algorithm. The main problem with machine learning methods is how to handle large functions with few samples. This results in model overfitting or poor performance when testing the model. Our goal was to avoid overfitting through the use of feature extraction and selection techniques. A key contribution to this research is the combination of the CNN feature extraction technique with the genetic algorithm of the feature selection technique. This combination results in active functions that are extracted from the input data related to the classifier. In addition, we have concluded that the SVM classifier gives fast and accurate results with fewer training datasets, as its modest technique is proposed to separate two discrete finite groups A and B into n-dimensional space. The combination of these methods then leads to a robust model that provides remarkable results when compared to other known studies.

In the future works, the researcher advises to apply other optimization algorithms that published in the last years instead of genetic algorithm to obtain new results which can be effective with COVID-19 detection.

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