CONVOLUTIONAL NEURAL NETWORK FOR SMART HEALTHCARE – A SURVEY ON ENHANCING RESOURCES IN DEVELOPING COUNTRIES

Abstract

Now days, it is a challenge to provide effective resources for health- care in resources-poor environments mainly in the developing countries. Health care systems are utilizing the advantages of deep learning techniques. Convolution neural networks (CNN) is one of the deep learning techniques helps to improve healthcare system by imaging, solving human resources crisis and reducing cost. This chapter focuses on basic concepts of convolutional neural networks, its methodology and how healthcare in resources-poor settings can be improved by early detection of diseases and effective treatment. This chapter also presents different kinds of application systems developed using CNN to minimize the patient waiting time, to give health assistance to patients and to reduce the burden of maintaining health records, adding caption to a medical image and assigning appropriate code to particular disease. Therefore, we explored the benefits of CNN in healthcare and discussed some of the architectures of CNN.

Keywords: Artificial Intelligence, Convolution Neural Networks, Healthcare, developing countries.

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I. INTRODUCTION

Health care is well-grounded as the domain related to the reestablishment of human life which is holistic including emotional, physical, spiritual and social wellbeing, the medical vocabulary defines health care as "The prevention, treatment and management of illness and the preservation of mental and physical well-being through service offered by the medical and allied health professions" [1]. All materials, facilities, funds, personnel and anything else which can be used for providing healthcare services are called as resources of healthcare. As everyone needs the healthcare, there is a great demand for it. The word "resource-poor" specifies an area where the potential to impart care for critical diseases is inadequate compared to basic care resources. The word "resource-poor" specifies an area where the potential to impart care for critical diseases is inadequate compared to basic care resources [2].

Improving the healthcare condition confer to healthier people. The complications involved in providing high-quality care are usually same over different health administrations. But the procedures used to reduce these complications and improving quality of healthcare are different in various resource-poor environments.

The factors to consider while improving health-care standard in resource-poor environment are the relationships among the patient, healthcare assistant and nonclinical workers in the health system, the essential staff, data resources and practice, administration and management system [3].

Whenever the situation of healthcare in developing countries is considered there are many challenges faced to bestow healthcare service to its people such as cost, economic, social, political and cultural constraints. The developing countries struggles to provide better services and minimize cost of healthcare given to its population. the difficulty with human resource in healthcare is the scarcity of health personnel for instance doctors, nurses and other experienced persons, and those who are available have insufficient practice and incompetent. Many communities have problems in availing healthcare services which perhaps related to distance from community to the healthcare, scarcity of money to spend for transportation and healthcare facility [4].

AI is a fastest growing specialization of information technology which has been extensively applied in the medicine. It enhances the degree of expertise and effectiveness of health tasks, besides preventing medical miscalculations. Several researches have demonstrated that the use of AI medical strategy could improve the healthcare results in rural regions of developing countries [5].

Topol has presaged that "almost every type of clinician, ranging from specialty doctor to paramedic, will be using AI technology, and in particular deep learning in the future" [6] Obtaining knowledge and working intuitions from complicated, high-dimensional and disparate medical science data remains a fundamental challenge in changing healthcare. There are different kinds of data emerging in the field of medical science such as electronic health records, diagnostics, sensor data and transcript, which are complicated, high-dimensional, badly interpreted as well as unorganized.

Conventional machine learning approaches usually performs feature engineering first to obtain the significant, robust and powerful features from the data and then set up either classification or clustering models upon those features. Several challenges are involved at both stages in the situation of complex information and insufficient field knowledge. Although, machine learning existing models have been used in many disciplines but have not been broadly implemented in medicine.

However, the recent improvements in deep learning technology has rendered effective paradigm to obtain persistent learning models from complex and huge data. Although the deep learning techniques are not analyzed largely for a wide variety of medicine issues.

Deep learning, which is distinct from classical machine learning in the way the models are trained from the raw data. Indeed, deep learning enables statistical methods that consists of several transforming layers evolved from neural networks to grasp representations of data at different levels of abstraction as shown in fig.1.

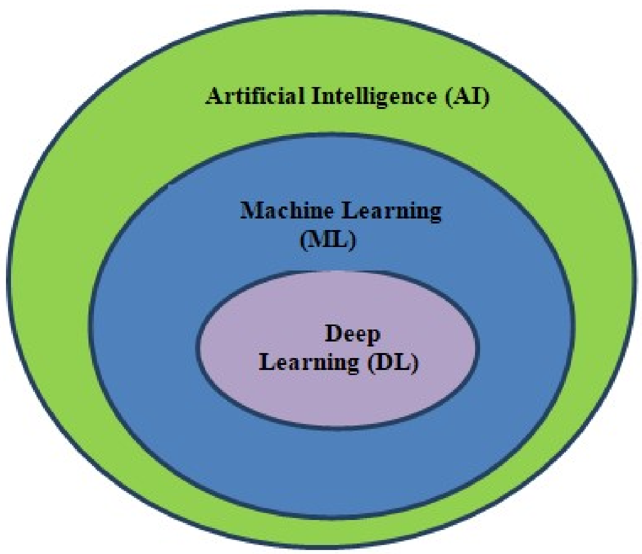

Figure 1: Representation of AI, ML and DL

The main distinctions among deep learning and the conventional artificial neural networks (ANNs) are the numerous hidden layers, their interconnections and the capacity to grasp relevant generalizations of the inputs. Actually, conventional artificial neural networks are typically restricted to 3 layers and are learned to get optimized descriptions for the individual task only which are not generalizable. But in deep learning every layer generates a representation of the perceived patterns on the basis of data it received as inputs from the preceding layers, by enhancing a confined unsupervised specification [7]. The fig. 2 below shows both the artificial neural network and deep neural network.

The layers of features of deep learning are not devised by human engineers, but they are learned from the data using a common learning strategy [8]. Some of the prominent achievements of deep learning have been in the area of computer vision. Computer vision main aim is to focus on image and video interpretation, deal with the tasks of object identification, classification and segmentation, which are helpful in finding whether a patient's radiograph includes cancerous tumors.

Convolutional Neural Networks (CNNs), a kind of deep learning algorithm developed to manage data that discloses intrinsic spatial invariance (eg images, whose meanings are unchanged under conversion), have advanced to be predominant in the field of computer vision. Medical imaging can considerably take advantage from recent progress in object detection and image classification. CNN-based methods have been proved successful for image-level diagnostics due to the fact that CNNs have accomplished human-level functioning in object-classification tasks because it learns to classify the object present in an image. Hence the Convolutional neural networks which is a kind of deep learning helps diagnose certain life-threatening diseases like cancer, early diagnosis allows to adopt healthy life style for survival and which also reduces the costs of treatment [9].

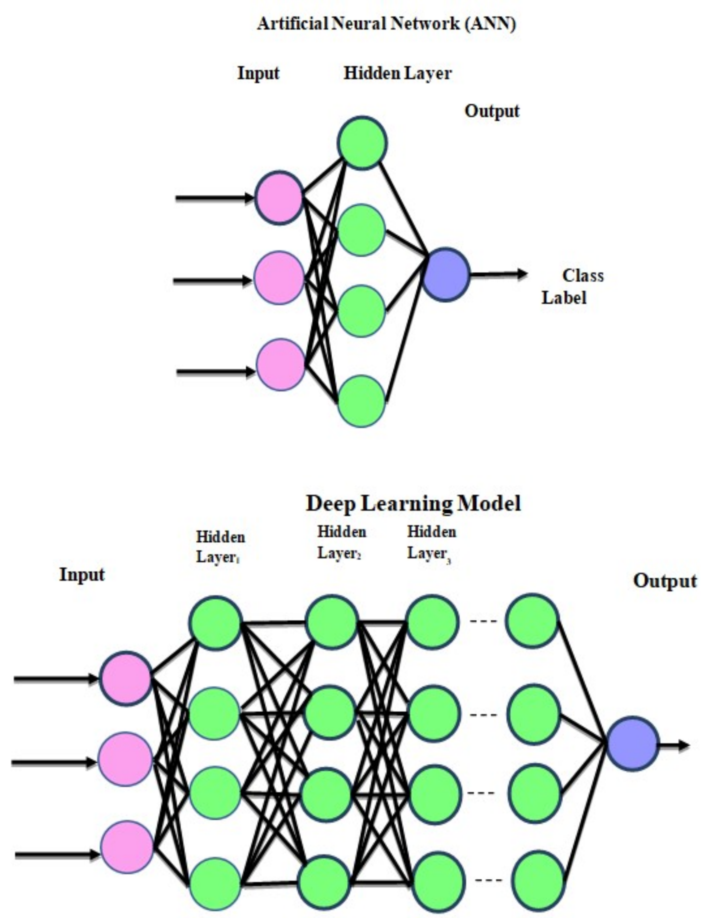

Figure 2: An interpretation of ANN and a Deep Learning Model

The remaining chapter is organized as follows. In sect.2 we present the architecture of convolutional neural networks and its components. Section 3 explains how convolutional neural networks are useful in improving the health care resources such as radiology where various CNN architectures are presented for medical image detection, segmentation and classification, human resources and reducing expenses. This chapter concludes with section 4.

II. CONVOLUTIONAL NEURAL NETWORKS

A convolutional neural network (CNN) also termed as a ConvNet is an artificial neural network includes several convolutional layers which are also called conv layers. This type of layer allows a deep learning model to systematically manage spatial patterns, which is effective in the applications of computer vision [10].

1. **Convolution Layer:** Convolutional layers comprise a set of kernels, which are also called as filters. Each kernel is a short window (known as a patch) that examines across the image (means convolves), from top left corner to bottom right corner.

   A kernel is a small matrix used for edge detection, embossing, blurring, sharpening and more which is achieved by performing a convolution among a kernel and an image. Kernels are consisting of weights which are learned through back-propagation. Each kernel varies in size but a standard size is 3X3.

   For example: MNIST monochromatic digits, the 3X3 pixel would made up of (width X height X color channels) 3X3X1 weights – 9 weights and 10 parameters (each convolutional filter possesses a bias term b). If operating with RGB full-color images, then 3X3X3 weights- 27 weights and 28 parameters.

   The kernel captures several distinct positions over an image as it convolves. Convolutional kernels contain inputs, weights and a bias; a weighted sum is calculated using an equation (1) and the result is passed across nonlinear function to generate an activation.

   $$z = wx + b \qquad \text{equation (1)}$$

   Expressing 3X3 pixels as inputs x and 3X3 kernel as weights w, the weighted summation is calculated in which mathematical products are computed elementwise depending on horizontal and vertical positions.

   Utilizing z, an activation value a is calculated by passing z through the selected nonlinear function such as the ReLU or the tanh function.

   Generally, there are multiple filters present in a convolutional layer, where each filter allows the neural network to gain a representation of the input in a distinctive manner for example, like simple cells in the morphological vision system, if the initial hidden layer in the neural network is a convolutional layer, it may contain a filter that reacts to vertical lines. Therefore, whenever it slides over a vertical line in an input image, it results into a large activation value [10].

For example,

$w.x = .01*.53 + .09*34+.22*.06+(-1.36)*.37+.34*.82+(-1.59)*.01+.13*.62+(-69)*.91+1.02*.34$
$= -0.7385$

.01	.09	.22
-1.36	.34	-1.59
.13	-.69	1.02

Kernel Weights

*

.53	.34	.06
.37	.82	.01
.62	.91	.34

Pixel Input

Next using Equation 1, we add bias term b (say, 0.20) to get z:

$z = w.x + b = -0.7385+0.20 = -0.9385$

Further filters in this convolutional layer can gain a representation of other elementary features like horizontal lines and color mutations. This is why these kernels are known as filters, which slides over the image and filter out the region of particular features, resulting in high activations when they discover the pattern, state and shade that are especially adjusted to detect. It produces a 2D array of activations which specifies where that filter's certain feature persists in the actual image. That is why, the output from the kernel is known as activation map. The fig. 3 shows how each and every element in activation map is calculated using input image pixels and kernel weights.

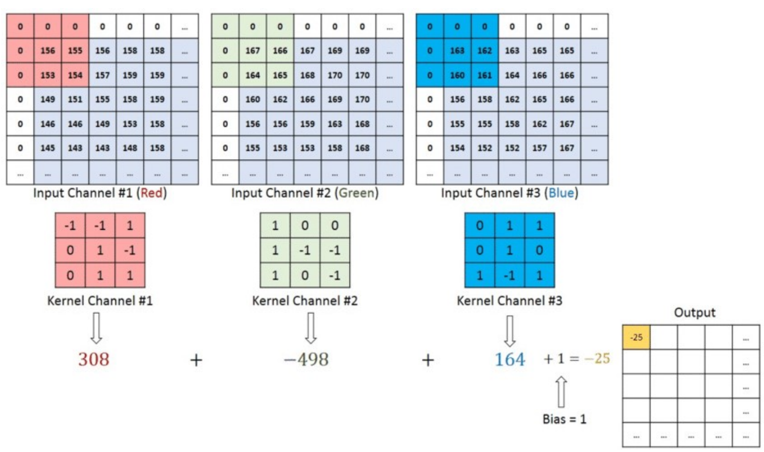

Figure 3: Example of calculating activation map element [source: towardsdatascience.com][11].

Similar to the hierarchical illustration of biological vision structure, successive convolutional layers get these activation maps as the inputs. Simultaneously the network becomes deeper, the filters respond to more and more complicated fusion of these elementary features, learning to represent abstract spatial structures gradually and finally constructing a hierarchy through lines and colors up to complicated forms and shapes as shown in fig. 4.

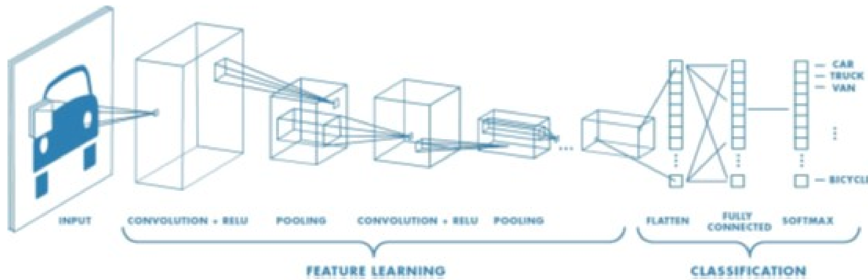

Figure 4: A Convolutional Neural Network Architecture [source: mathworks.com][12].

- **Filter Hyperparameters:** There are few hyperparameters, which prescribes several weights and biases corresponding to specific convolutional layer.

  - **Kernel size:** the common size for any kernel is 3X3, although kernel size of 5X5 pixels is also prevalent and 7X7 is broad. With reference to image, if the kernel size is very big, there would be many challenging features in the region of visual space and it is very competent for the convolution to learn efficiently, if the region is very small (e.g., 2X2) it would not be in a position to adapt to any structure, which is neither helpful.

  - **Stride length**: it signifies the magnitude of the step that the kernel requires as it scans over the image. Most frequently stride length of 1-pixel is used. Sometimes stride length of 2-pixels is also used but stride length of 3-pixels is rare. If larger stride length is taken then the kernel might miss out the significant parts of the image that are of use to the model.

  - **Padding:** It is needed to generate an activation map that is similar to the size of an input image by placing zeros all over the edges. For instance, if an image size is 28X28 and the kernel is 5X5, padding with 2 zeros all over edges will generate a 28X28 activation map.

The equation for activation map is

$$Activation\ Map = \frac{I-K+2P}{S} + 1 \qquad \text{equation (2)}$$

Where:

I is the image size
K is the kernel size or filter size
P is the padding size
S is the stride length

Therefore, the activation map with the 2 zeros padding is of 28X28:

$$Activation\ Map = \frac{I-K+2P}{S} + 1$$

$$Activation\ Map = \frac{28-5+2(2)}{1} + 1$$

$$Activation\ Map = 28$$

These three hyperparameters are interrelated, hence when designing the CNN architecture, these values should be chosen carefully to get the reasonable activation map size.

2. **ReLU:** It is a Rectified Linear Unit and is a nonlinear function: f(x)=max (0, x). x is an input to the neuron. The output given is same as input, if positive, otherwise it gives zero as shown in fig 5.

   This is usually applicable unit-wise to the output of a distinct function, like matrix-vector multiplication. All negative values are replaced with zeros in the feature map in order to introduce non-linearity in the network, because most of the data in real-world that is to be learned is non-linear.

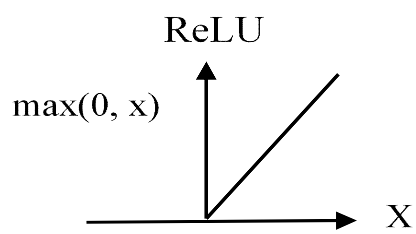

Figure 5: ReLU activation function

3. **Pooling Layer:** Pooling layer is a layer type, which is primary in computer vision neural networks which works in sequence with convolutional layers. It reduces the number of parameters progressively and calculations in the neural network. It helps to avoid overfitting. A pooling layer has a stride length as well as a kernel size similar to convolutional layers and also it slides on top of the input image. It applies a data-reducing operation at each location it captures in the image.

   The pooling layers usually use the max operation, and are called as max-pooling layers. They keep the largest value inside the receptive field and remove the other values.

Example:

1	2	1	4
5	2	2	6
3	0	3	2
8	4	2	1

→

5	6
8	3

Generally, a pooling layer has a filter size of 2X2 and a stride length of 2. At each location pooling layer assess only 4 activations, keeping only the largest value and hence, downscaling the activations by an element of 4

4. **Fully Connected Layer:** In a neural network, fully connected layers are those layers where preceding layer neurons are interconnected to each and every neuron of the next layer. The activations can be calculated with a matrix multiplication along with a bias offset. The result of each convolution/pooling layer is flattened into a single vector which represents a probability of a particular feature belongs to a particular label as shown in fig.6.

   For example, if there is an image of a car, representing features like engine, four-wheeler, leather seats should have the high probabilities for the category "car".

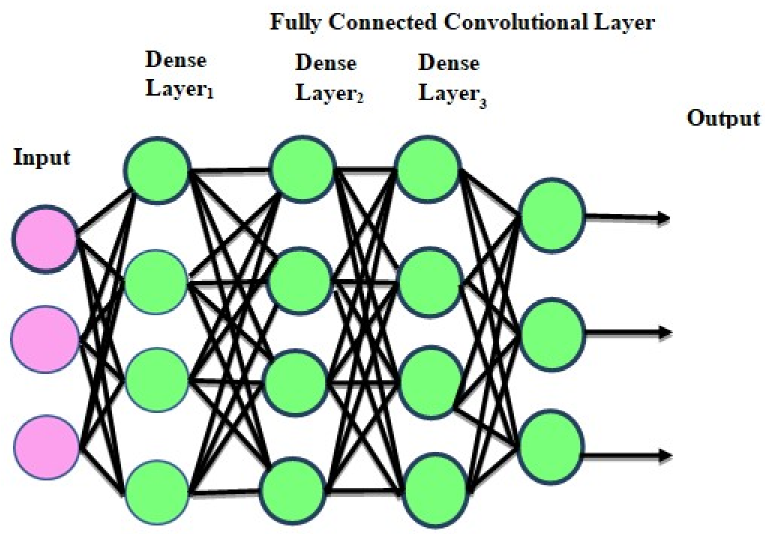

Figure 6: Fully Connected Convolutional Neural Network

5. **SoftMax layer:** The SoftMax layer often used in the final layer of a neural network which transforms all the activations into a series of probability values to predict a category [10].

III. CONVOLUTIONAL NEURAL NETWORKS IMPROVING THE HEALTHCARE RESOURCES

Convolutional Neural Networks applications in healthcare includes clinical diagnosis, prediction of cancer, image investigation and interpretation. Non-clinical applications involve enhancement of healthcare administration management [13].

1. **Convolutional Neural Networks in Radiology Tasks:** Computer vision problems that are specifically relevant to imaging discipline contains detection, classification and segmentation as well as for image optimization. Detection enables to recognize the region of organs, nodules, tumor or other elements of attention for instance, finding location (x, y) parameters of hepatic tumors in liver. Classification is nothing but assigning label to images belonging to a particular class, for example, chest X-ray is categorized as either

normal class or having characteristics tuberculosis. Segmentation is the procedure to find the boundaries of 2D or 3D medical images for example, pixel-wise edges of organs or pathologic attribute. Image optimization have problems like enhancement, formulation of input. All these techniques are illustrated in the fig.7.

Particular task needs particular metric to show the results. For detection true-positive and false-positive probability metrics are considered, classification uses ROC curves and segmentation uses Jaccard index or dice coefficient as metric used to measure the result [14].

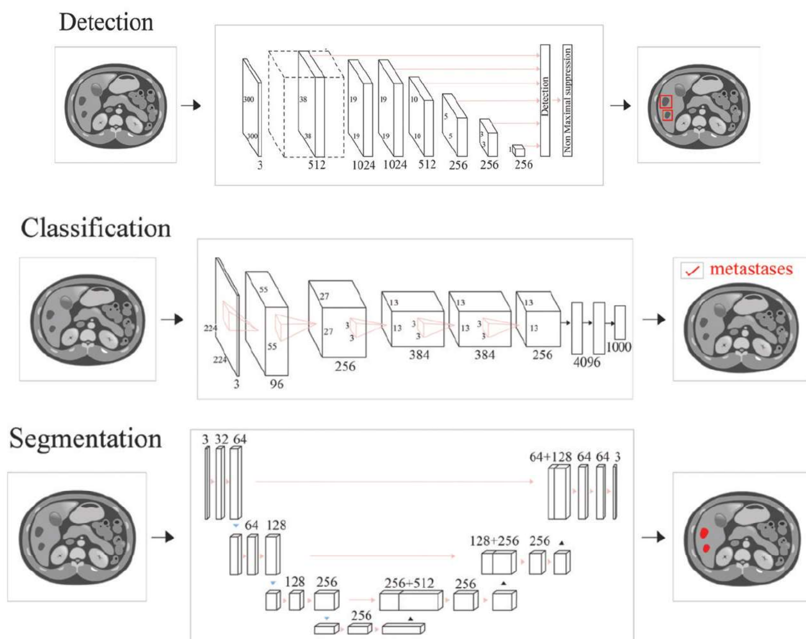

Figure 7: A representation of Detection, Classification and Segmentation tasks by CNN for an image.

- **Tuberculosis Diagnostics:** Tuberculosis (TB) is a dreadful and contagious disease which infects majorly to the downside population and needs complicated medication scheme. It is an unresolved crucial health problem worldwide with exceeding 9 million approximated latest cases and 1.5 million demise in an average 365 days [15]. Nearly 80% of the population are from the Western Pacific, South-East Asia, and African who developed TB in the year 2013 [16]. Mostly the contagious population was from poor facilities and diminished societies with fragile health management system. The global health association has handled the scenario by generating and assessing effective vaccines, enhancing the disease confirmation procedure, and encouraging the sufferer abidance to the medicine regime. The delay in TB diagnosis should be reduced, to alleviate the disease spread and minimize the generative rate of the tuberculosis outbreak.

Target is to minimize the disease diagnosis waiting time using socio-technical method. Designing a user friendly, cell phone based assessing application to possibly speed up the process of tuberculosis confirmation by emerging new image processing and deep learning methods to explore the chest X-ray representation.

To examine the X-ray pictures and to cover the chest radiology image with enhanced perfection and better uniformity. The screening problem is converted into a classification problem. Especially, an exploration of convincing and competent models needs to be explored to divide the picture into mini portions and classify the image area into distinct classes of tuberculosis indications (e.g., Miliary pattern, Bronchiectasis, lymphadenopathy, cavitation and etc.).

Several CNN models and training constants are evaluated for TB X-ray image database. Transfer learning approach applied in chest X-ray images and finetuned the pretrained CNN model parameters to identify TB and find its potency and competence. The CNN model pretrained with ImageNet dataset [17].

A simple framework for TB classification employs LeNet [18]. A CNN architecture generally encompasses several layers as shown in fig. 8. CNN understands the parameters from an extensive data to consider the local and global properties in the image and Every framework has different kind of layers and activation functions to present robust quality illustration capability than human-managed attributes [19].

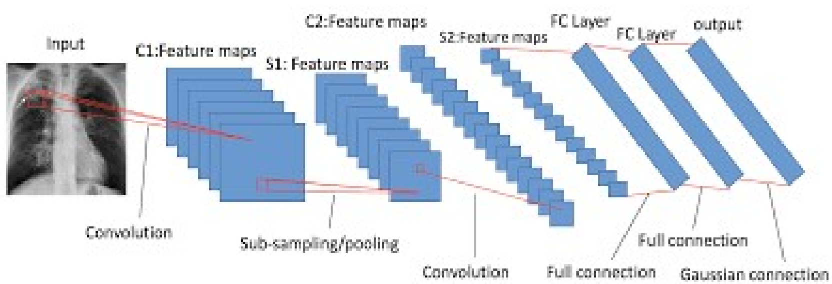

Figure 8: CNN architecture for Tuberculosis Classification [19].

It is also possible to filter and ascertain the chest X-ray image include tuberculosis or not using AlexNet, which is a binary classification problem.

- **Lung Cancer Detection:** Lung cancer is the kind of usual cancers, which is a reason for above 225 million cases, 150 million fatalities and $12 billion costs in healthcare per year in the U.S [20]. In U.S, only 17% of the people determined with lung cancer live for five years, and the chances of existence in the underdeveloped nations is very less.

  The stages of cancer define how far it has spread in the body. Initial and secondary stage indicates the cancer confined to respiratory system and advanced condition of malignancy indicates that it has extended to other organs. Common procedures of cancer diagnosis are imaging like computed tomography (CT) scans and biopsies. Initial investigation of respiratory malignancy increases the chances of existence, though it is very complicated to identify because of less symptoms.

A binary classification task needs a precise classifier specifically 2D and 3D CNN for identifying the existence of respiratory malignancy in Computed Tomography scans of patient. A convincing classifier might possibly speed up and lessen the expense of lung cancer scanning, enabling quick and early identification and enhances life span. The main purpose is to build a computer-aided diagnosis (CAD) framework which obtains the ill person 's chest CT scan as input and gives results [21].

The CAD approach must identify the existence of a small nodule (if diameter <10 mm for initial stage) from a 3Dimensional CT scan of lung (mostly of size 200 mm X 400 mm X 400 mm). A 2Dimensional segment of a CT scan reveals an initial phase lung cancer in the fig. 9.

Figure 9: 2D CT scan portion comprising a mini(5mm) lung cancer nodule

A Computed Tomography scan is penetrated with errors from nearby tissues, air, bone. This noise has to be removed by preprocessing, so that the CAD can easily identify the nodule. Therefore, the classification consent is image preprocessing, nodule identification and cancer classification. The comprehensive techniques need to be applied to obtain the convincing nodules to improve the accuracy of lung cancer identification.

U-Net is a 2-dimensional CNN structure as shown in fig.10 used for segmentation of medical image. It takes input as minimum regions of interest in spite of the entire divided 3-dimensional image. U-Net trained on the LUNA 16 dataset and tested on 2D portion of Kaggle data to present precise locations of all the nodules and mention them as positive for lung cancer. But the U-Net also gives a lot of false positives, which leads to employing an additional classifier to discover the malignancy.

The regions around nodule identified by U-Net are given as input to 3D CNNs to categorize the Computing Tomography scans as either positive or negative for lung malignancy.

A 3-dimensional CNN is employed as a linear classifier which utilizes SoftMax cross entropy loss and Adam optimizer using ReLU function and dropout besides every convolutional layer at the time of training. The general framework of CNN is depicted in fig.11.

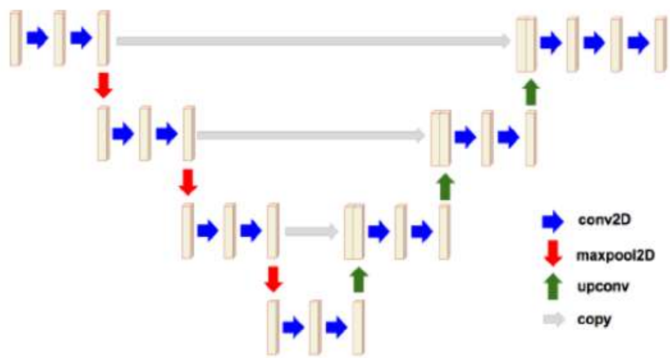

Figure 10: U-Net structure

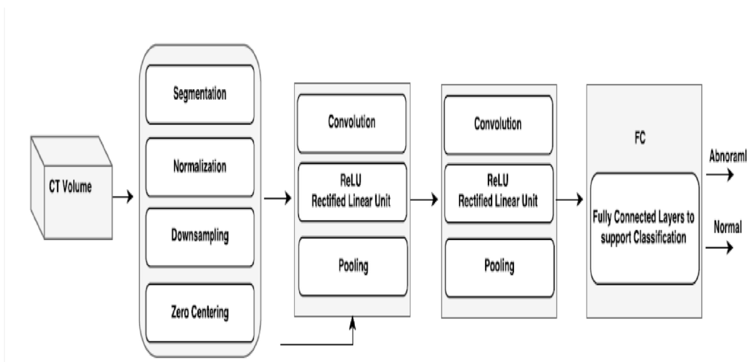

Figure 11: 3D CNN architecture

A representation of 3D CNN is shown in figure 11 and examined in detail in the table1.

Table 1: 3D CNN architecture in detail

Layer	Params	Activation	Output
Input			28 × 28 × 28
Conv1	5 × 5× 5	ReLu	28 × 28 × 28× 7
Max Pool	1× 1× 1, stride 2× 2× 4		14 × 14 × 7 × 7
Conv2	5 × 5× 3	ReLu	14 × 14 × 7 × 17
Max Pool	2× 2 × 2, stride 1× 1 × 0		6 × 6 × 3 × 17
Dense			256
Dense			2

The advantage of having minimum labelled information for particular malignant type could make it evident for different types of cancers [22].

- **Brain MRI Segmentation:** From the past few years, brain Magnetic Resonance Image (MRI) segmentation has been in demand in the area of computer vision. Segmentation act as a significant step in brain MRI analysis and brain disorders research. Evaluation of systematic inequality by measuring capacity of region of interest, can be utilized to find the severity of disease or growth in brain [23].

  MRI segmentation plays a significant part in medical image processing and analysis. There are many segmentation methods evolved which are usually edge-based and contour based [24]. But it is very difficult to segment complicated form of medical image with excellent accuracy [25].

  Brain Magnetic Resonance Image segmentation with the conventional techniques are time-taking and demands preparatory medical knowledge. Patch-based CNN grasps the given brain MRI patches as input. The center pixel is used to determine the label of the patch. The stride is initialized to one pixel in dividing patches. Biased intersecting is possible in adjoining patches as shown in figure 12 below: It obtained improved accuracy in segmentation with patch-based CNN in figure 13 [26].

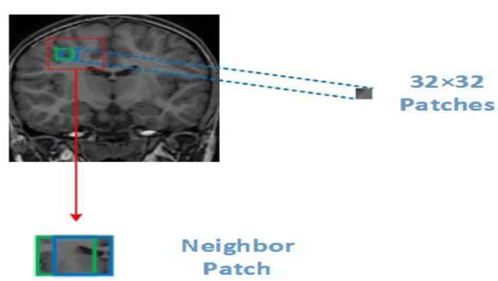

Figure 12: Segmentation of brain MRI. 32X32 patches given as input to CNN.

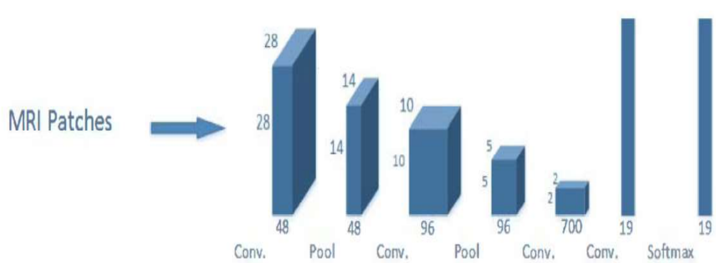

Figure 13: A CNN architecture for MRI patches

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- **Heart Attack Detection:** Heart disease is a kind of life-threatening diseases. As stated in data provided by the World Health Organization (WHO) [27]. Billons of population across the world encounter with heart disease and out of it around 12 million are dying each year. The key cause for such deaths is that the disease is not recognized at an initial stage. Identification of heart disease in the initial stage play an essential role in the reliable and beneficial treatment to the sufferer. Hence, it is necessary to develop a system that recognizes the disease at the early stage with better accuracy and reduced operational cost.

  A fundamental CNN framework is constructed for categorization of heart disease images. This model is trained straightaway with heart disease images instead of pre-trained networks employing transfer learning. GoogleNet and AlexNet are the pre-trained networks extensively used in the applications of image processing.

  Medical images vary crucially from non-medical images. The elementary structure of this simple CNN model comprises several layers. The input layer is the primary layer of the CNN structure. The convolution layer shrinks the attribute values of the actual image database through convolutional kernels. A feature map is generated by sliding convolutional kernels at all positions of the input image. The max pooling layer is utilized to scale down the feature map by keeping only few important features, which aims at increasing the learning procedure. There are 2 nodes in the fully connected layer from the preceding layer which indicates there are 2 classes, each node for each class, that is “cardiac arrest with infarct” and “cardiac arrest without infarct”. The SoftMax resolve the classification assignment, which is set before the output layer, which also has 2 nodes. The output layer is the final layer of this framework which classifies the heart disease image into one of the 2 categories. A simple CNN straightaway trained with medical images than with the pre-trained networks is preferable for medical image processing [28].

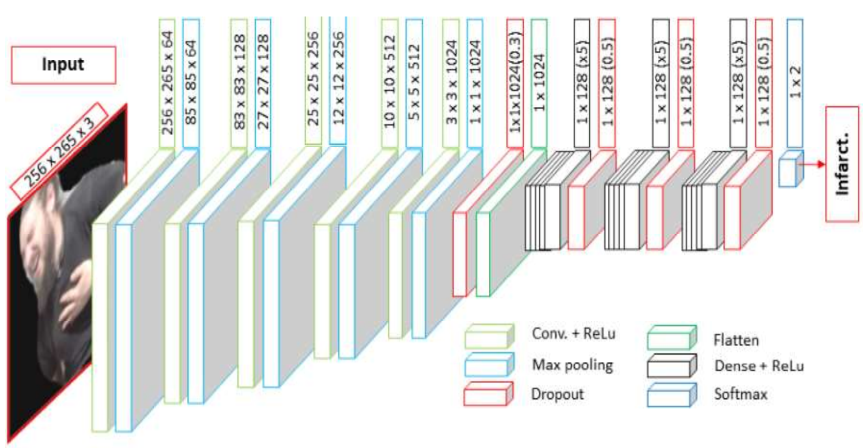

Figure 14: A CNN architecture for classifying image into classes either cardiac arrest with infarct or cardiac arrest without infarct [29]

- **Skin Cancer Detection:** Skin cancer contains anomalous variations in the exterior surface of the skin. This is indeed the common malignant in the society and restrain nearly 75% of the society's cancer.
  However maximum people get cured after treatment but still it is vital distress because of its pervasiveness. [30].

  Many skin cancers spread only regionally and occupy alongside tissues, but part of them, mainly melanoma, which is the scarce skin cancer type spreads by means of circulatory system or lymphoid system and influence the extreme end of the physical structure [31] which causes death. The Melanoma diagnosis in the early stages can remarkably reduce the fatality rate but the diagnosis of this cancer at the initial stage is very difficult, even for specialists. An effective method to identify melanoma cancer in the initial stage is needed to save the lives of people suffering from this cancer.

  Fig.15 shows an elementary skin cancer identification using typical CNN. The convolutional layer assesses the result of the neurons that are attached to the restricted area in the input. The computation is done by product of weights of every neuron and the area they are attached to. The pooling layer subsamples the given picture to minimize the computation process, storage and the various parameters. Minimizing the magnitude of the given picture makes the network less effective towards picture rearrangement. The output layer has two labeled images consisting of 1(cancerous region) or 0(background region). The CNN acts as a binary classifier to classify the given input image into either malignant or benign [32].

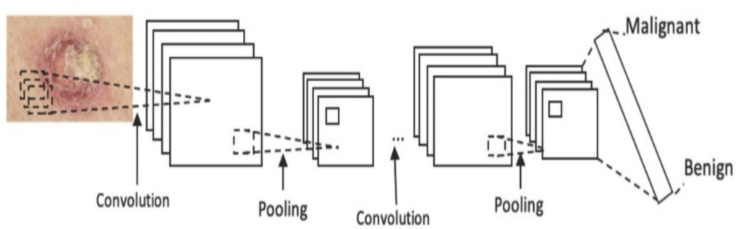

Figure 15: Skin cancer detection using convolutional neural network

2. **Convolutional Neural Network for Improving Human Resources Deficiency:**
   Referring to human resources of medical management, such as clinical and non-clinical workers, who are answerable for community and self-standing involvement. It is necessary to maintain the stability among human and physical resources, distinct health supporters and caregivers to guarantee the system's attainment. Human resources management exercises are necessarily implemented which is beneficial to obtain the significant stability of workforce and the proficiency of the specialist efficiently and convincingly. A specialist, who does not have enough appliance is as incapable as having the appliances without the specialist [33].

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- **Smart Hospital and Patient Scheduling System:** Now-a-days, the major concern about the healthcare system is to maintain and manage good relationship with the patients because the waiting time problem in hospitals and health centers are expanding gradually. There are many schemes initiated by hospitals to manage with patient's waiting time in some way. Nonetheless, an everlasting way out is needed to address this matter that enables the patient to get relaxed when arriving for therapy. The current healthcare environment needs efficiency and patient consent for best performance. In developing countries, the out-patient section of many healthcare systems is encountered with many issues.

  To overcome the above-mentioned situation a novel decision-making system is presented to support patients to get relaxed when visiting to clinic without any trouble to consult doctor. This system is based on CNN for the better medical schedule is done through four levels. Initially, electronic health record (EHR) framework's booking information is gathered and preprocessed. Secondly, process discovery is performed to gain significant outcomes, arrival rate and service time examination is done. Thirdly, considering these outcomes, a model is built and assessed to confirm whether the model performs as is examined from the information provided.

  Finally, decision support for process improvement. Therefore, this decision support system utilizing CNN reduces the delay by booking arrangement of the specialist [34].

- **Intelligent Health Assistant:** Healthcare is more important for living a quality life. But unfortunately, due to our brisk life, it is sometimes problematic to consult a doctor for our non-fatal diseases. The idea of chatbots or personal assistants is developed based on advanced areas such as AI and ANN.

  A healthcare assistant enables the users to monitor for symptoms of usual diseases, an advice to go to see doctor if necessary, exercise guidance, follow exercise or workout regime.

  The main intention behind developing the intelligent health system is to improve the quality of living of people who have busy work schedules to comfortably control their health. In this system, CNN is employed for identifying the purpose of the message to label and initiate the particular action to answer the user. The response is produced based on the user's information, health archive, and the instant input of the end user [35].

3. **Convolutional Neural Network for Reducing Cost:** The convolutional neural networks can be used to generate captions automatically for a given medical image and assigning ICD-9 codes through examining the medical records which do not require any health worker to perform these tasks which indirectly reduces the cost.

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- **Automatic Caption Generation:** With the accessibility of a huge datasets and an increase in high performance computing, it is necessary to have effective techniques to obtain pertinent features from an image and predict one or more chronologies of textual representation, which needs the combination of natural language processing and computer vision methods

  Image captioning has gained a lot of attention and it is one of the tasks in the Artificial Intelligence (AI) field, where the aim is to develop a model capable of getting insights of an input image and produce a natural language caption describing an image as output.

  Medical images are used for disease diagnosing and treatment. Considering medical experts have restricted time to note down diagnostics reports description to state the findings on the increasing number of medical images causes several problems such as overlook finding, varying analysis of observations and stalling the stay of a patient in the hospital which rises the treatment cost.

  With the rise of medical images from various techniques like MRI, X-rays, computed tomography(CT) scans etc. and the growth in power of graphics processing units, it is certainly time to explore the benefits of automatic caption generation methods to present valuable information, lessen work burden, and offer capacity for quick and more systematic description, which speeds up the procedure of diagnosis. Many existing works take maximum advantage of the encoding and decoding architecture of RNN and the deep CNN.

  In which, from a given image CNN extracts the key features in the form of fixed-size vector. Recurrent Neural Network or its alternatives like Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), are availed as language frameworks, to interpret the fixed-size vector gained from CNN to suitable sentences that are meaningful and grammatically right [36] as shown in fig. 16.

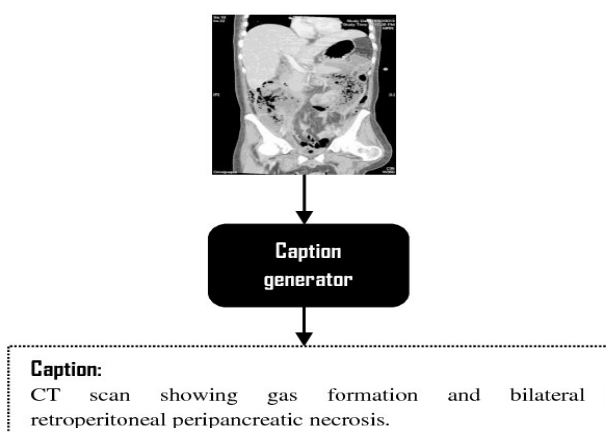

Figure 16: Automatic caption generation using CNN

- **Automated ICD-9 Coding:** With the exponential growth of medical field, International Classification of Diseases codes ninth revision (ICD-9) is broadly depleted to represent a patient's investigation containing evidences, inquiry of fatality percentage and medicative compensation. Every disease has an individual ICD-9 code and utilized in the EHR as an invoice system. ICD-9 keys are generally handled by the programmers of the healthcare system's Medical Record Department who reserve ICD-9 keys to pharmaceutical records in line with doctor's clinical result. The coders need to have good knowledge of medicine field, coding conventions and medical terms. Although, tactical coding is high-priced, time taking and ineffective. In view of these confinements, it is necessary to establish a convincing statistical perspective for programmed ICD-9 coding.

  Recently, the deep learning procedures, especially convolutional neural networks (CNN) have been proven very convincing for machine vision system, the major benefit of CNN is its potential of automatic disclosure of image local features. The local features are important for automatic ICD-9 code allocation from the hospital discharge statement.

  CNN is used to acquire local attributes from case records. Conversely, the global attributes are as well important for automatic ICD-9 code allocations. Document to Vector (D2V) is an unsupervised learning procedure for automatically allocating ICD-9 codes. DeepLabeler, as shown in fig.17 is a deep learning structure which integrates both CNN and D2V to extract local and global features to assign ICD-9 codes [37]. A list of ICD-9 coding is shown in fig 18.

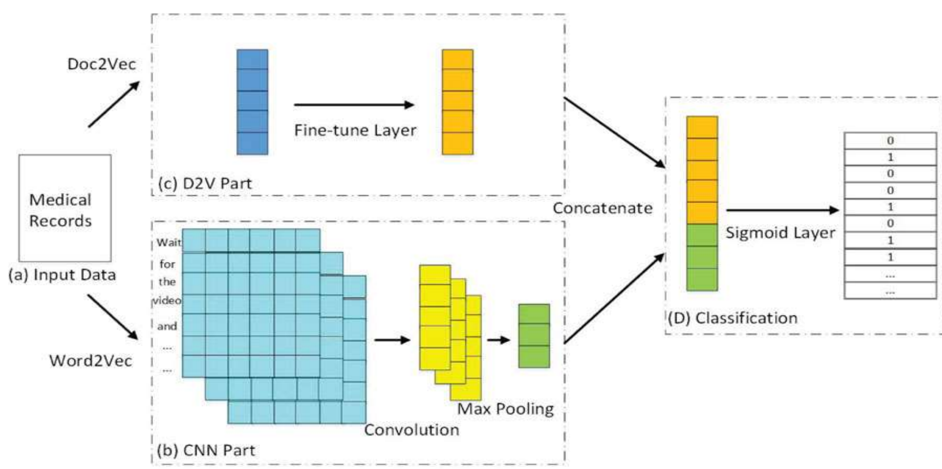

Figure 17: DeepLabeler method

414.8	OTHER SPECIFIED FORMS OF CHRONIC ISCHEMIC HEART
414.9	CHRONIC ISCHEMIC HEART DISEASE UNSPECIFIED
416.1	KYPHOSCOLIOTIC HEART DISEASE
416.8	OTHER CHRONIC PULMONARY HEART DISEASES
416.9	CHRONIC PULMONARY HEART DISEASE UNSPECIFIED
426.6	OTHER HEART BLOCK
428.0	CONGESTIVE HEART FAILURE UNSPECIFIED
428.1	LEFT HEART FAILURE
428.20	UNSPECIFIED SYSTOLIC HEART FAILURE
428.21	ACUTE SYSTOLIC HEART FAILURE
428.22	CHRONIC SYSTOLIC HEART FAILURE
428.23	ACUTE ON CHRONIC SYSTOLIC HEART FAILURE
428.30	UNSPECIFIED DIASTOLIC HEART FAILURE
428.31	ACUTE DIASTOLIC HEART FAILURE
428.32	CHRONIC DIASTOLIC HEART FAILURE
428.33	ACUTE ON CHRONIC DIASTOLIC HEART FAILURE
428.40	UNSPECIFIED COMBINED SYSTOLIC AND DIASTOLIC HEAR
428.41	ACUTE COMBINED SYSTOLIC AND DIASTOLIC HEART FAILU
428.42	CHRONIC COMBINED SYSTOLIC AND DIASTOLIC HEART FAI
428.43	ACUTE ON CHRONIC COMBINED SYSTOLIC AND DIASTOLIC
428.9	HEART FAILURE UNSPECIFIED
429.82	HYPERKINETIC HEART DISEASE
429.89	OTHER ILL-DEFINED HEART DISEASES
429.9	HEART DISEASE UNSPECIFIED
659.70	ABNORMALITY IN FETAL HEART RATE OR RHYTHM UNSPEC APPLICABLE

Figure 18: A list of some of the ICD-9 coding [38]

IV. CONCLUSION

In this chapter we study the situation of healthcare in developing countries and exploit about the importance of convolutional neural networks in medical field. We discussed about the architecture of CNN and its components. We explored various CNN architectures used for imaging of certain diseases or tumors. We explained how CNN can be helpful in improving human resources and reducing cost. In future, it is possible to combine devices with chatbot for pursuing the innards and actions of end user. It will be exciting to explore the constraints of DeepLabeler and upgrade the coding power with other architectures like LSTM model and attention model. Hence, we presented a detail study of CNN for improving resources of healthcare system.

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