SEMINAR REPORT

ON

"Medical Image Analysis Using Deep Learning"

BY

Ms. John Annette Thankachan

Exam No: 71815316C

Under the guidance of

Prof. Shilpa Pimpalkar

DEPARTMENT OF COMPUTER ENGINEERING

ALL INDIA SHRI SHIVAJI MEOMRIAL SOCIETY'S

INSTITUTE OF INFORMATION TECHNOLOGY

PUNE 411041

SAVITRIBAI PHULE PUNE UNIVERSITY

2019-2020

AISSMS
INSTITUTE OF INFORMATION TECHNOLOGY
ADDING VALUE TO ENGINEERING

Approved by AICTE New Delhi, Recognized by the Government of Maharashtra and Affiliated to Savitribai Phule Pune University.
Accredited by NAAC with A grade

Department of Computer Engineering

CERTIFICATE

This is to certify that **MS. ANNETTE T. JOHN Exam No.: 71815316C** from **Third Year** II^{nd} **Shift Computer Engineering** has successfully completed his/her seminar work titled

"MEDICAL IMAGE ANALYSIS USING DEEP LEARNING"

at All India Shri Shivaji Memorial Society's Institute of Information Technology, Pune in the partial fulfillment of the Bachlors Degree in Computer Engineering

PROF. S. P. Pimpalkar
Internal Guide

PROF. GIRISH NAVALE
Seminar Coordinator

Seal/Stamp of the college

Dr. S. N. Zaware
Head of the Department
Computer Engineering

Place: PUNE
Date:

ABSTRACT

Medical images analysis is one of the most promising research avenues in today's time and age as it assists the diagnosis and medical prognosis of a number of ailments such as Cancer, Tuberculosis, MERS, COVID-19, Alzheimer's disease and the likes. The healthcare sector is unlike any other as it has an unmatched expectation of the highest levels of accuracy of diagnosis, care, and services, with very little to no room for errors. The interpretations and analysis of medical data in many places currently are being done by medical experts in the respective fields. This stands as a potential limitation, as the diagnosis is then subjected to various factors like the complexity of the image, the extensive variations of different interpreters, and human errors. The colossal success of machine learning algorithms at image recognition tasks in recent years intersects with a time of an extensively increased use of electronic medical health records and diagnostic imaging. This serves as a huge advantage as it is now possible to apply these machine learning algorithms to medical big data. With the help of this, we can identify significant hierarchical relationships algorithmically within the data with reduced manual labor and manpower. This report covers how different deep learning models can be applied to the EHRs and their applications of medical image classification, localization, detection, segmentation, and registration. This report also covers a case study of Breast Cancer detection using CNN. In the final section, the report also discusses various research obstacles, emerging trends, and possible future directions.

ACKNOWLEDGEMENT

I would like to extend my sincere gratitude to my project guide Prof. Shilpa Pimpalkar for her able and diligent mentorship and her insightful supervision throughout the course of making this seminar report, without whom this wouldn't have been possible. I would also like to thank Prof. Chetan Aher for his contribution and direction on understanding Latex which helped me to prepare this report. I would like to take this opportunity to thank our seminar co-ordinator, Prof. Girish Navale for his guidance. Furthermore, I'd like to acknowledge and appreciate all those who have supported and motivated me in this endeavor, especially my seniors, and my fellow classmates, all of whom have advised and helped me make adequate use of the right resources. A special thank-you to my family for their constant encouragement and moral support.

Ms. Annette T. John
AISSMS IOIT, Pune.

INDEX

List of Abbreviations

CNNs Convolutional Neural Networks

CT Computed Tomography

DBM Deep Boltzmann Machine

DBN Deep Belief Network

DNN Deep Neural Network

EHR Electronic Health Record

GAN Generative Adversarial Networks

GPU Graphical Processing Unit

HIPAA Health Insurance Portability and Accountability Act

ILSVRC Imagenet Large Scale Visual Recognition Challenge

MRI Magnetic Resonance Imaging

PET Positron Emission Tomography

RBM Restricted Boltzmann Machines

RELU Rectified Linear Unit

RNN Recurrent Neural Networks

SAE Stacked Autoencoders

SHRs Summary Health Records

US Ultrasound

List of Figures

List of Tables

Chapter 1

INTRODUCTION

Machine Learning algorithms have immense scope to be implemented in varying fields of medicine right from the discovery of drugs to medical decision making, thereby significantly revolutionizing the way medicine is practiced. Gone are the days when health-care data was limited. Due to the enormous advancements in image acquisition techniques, the data that is being generated now is quite large, which makes it challenging and also interesting for conducting image analysis. The success of machine learning algorithms thereby comes at an opportune period when the number of digitized medical health records is on the rise. The proportion of medical practices primarily engaged in direct patient care that uses electronic health records increased 17.56% between 2007 and 2013, from 25.0% to 68.9%, nearly a threefold increase. In 2015,Electronic Health Records(EHRs) were created for 91% of Canadians, and 91,000 clinical practitioners were using EHR based mechanisms [1]. England under the initiative "National Plan for IT" (NPfIT) modernized their Healthcare-system.Summary Health Records (SHRs) were created for 54 million persons (96% of the population)[2]. Around 90% of physicians in Germany are using EHR systems[3]. In New-Zealand,an EHR adoption rate of 97% was observed. [4]. Medical reports primarily in the form of images play an critical aspect of a patient's EHR and are presently being analyzed by human medical professionals, who are limited by certain factors like fatigue, accuracy, and experience. Therefore, the diagnoses' are prone to human error and may encounter variations across various experts. It takes years together along with great financial expenses to train a well-qualified radiologist. Certain health-care systems outsource their reporting to cheaper countries like India. An erroneous and delayed diagnosis can potentially cause great harm to the patient. Therefore, it is the need of the hour for analysis of medical images to be implemented with accuracy and efficiency using machine learning and deep learning algorithmic models. Owing to the labeled and relatively structured data at our disposal, analysis of medical images is an emerging field of research in deep learning . Deep learning will not only help to identify and extract features but also construct new ones, furthermore, it does not only diagnose the disease but also measures predictive targets and provides prediction models to help medical practitioners efficiently. This is also likely to be the first premise where patients would experience the working of artificial intelligence mechanisms and paradigms. This holds significance for two reasons: this would be a litmus test to check if AI can actually improve patient survival rate and, and it would also be a testing ground to check how well the general masses respond and trust life-altering health choices that are made or assisted by a non-human entity.

1.1 TYPES OF MEDICAL IMAGING

There are a number of ways to perform medical imaging. The use of mechanisms like Ultrasound (US), Computed Tomography (CT) scans, X-ray, Positron Emission Tomography (PET) scans, Magnetic-resonance Imaging(MRI) scans, histology slides, retinal photography, and dermoscopy have increased significantly over the years. Few of these modalities are used to study only certain specific specific organs (retinal photography, dermoscopy) while others are used to study multiple organs (such as CT, MRI). The amount of data generated and the resolution of the images also play a key factor regarding data pre-processing and algorithm design, memory and processor limitations.

1.2 HISTORY OF ANALYSING MEDICAL IMAGES

AI algorithms migrated from techniques based on heuristics to hand-crafted and manual feature-extraction methods and then finally to supervised learning paradigms. The scope of unsupervised learning models are also being researched, although majority of the algorithms in published literatures have employed supervised learning techniques like Convolutional Neural Networks (CNNs). Apart from the easy access of labeled and structured datasets, the factor that further enhances and upgrades the performance of these models are the advancements in hardware and Graphical Processing Unit(GPU). In it's basic sense, Artificial Neural Networks or ANN is an

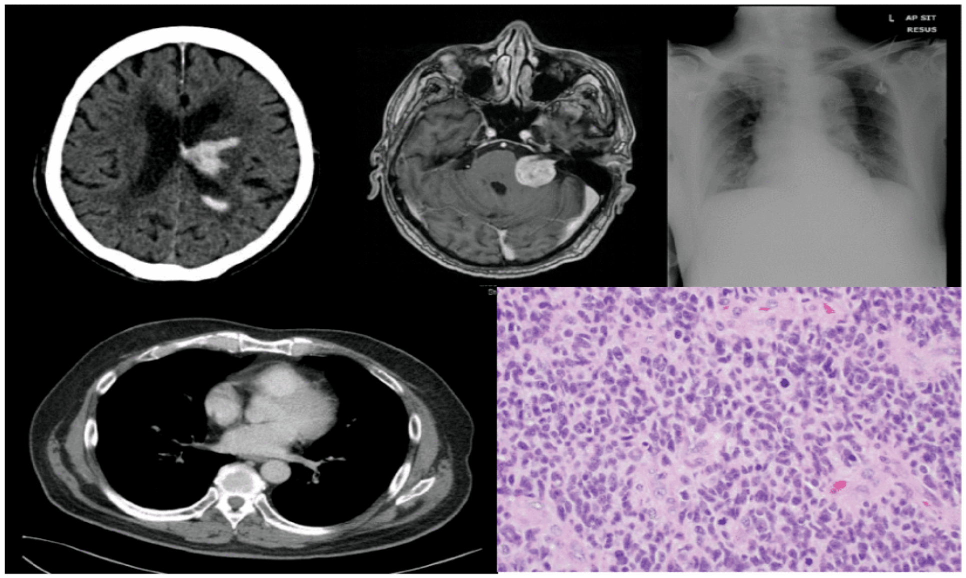


Figure 1.1: Collage of Medical images gathered from diffrent modalities like MRI, CT and X-ray

information processing paradigm that is inspired by the way the biological nervous system processes information. It is composed of large numbers of highly interconnected processing elements(neurons) working in unison to solve a specific problem. These interconnected neurons form multiple layers of neural networks, that create a deep neural network. These networks are capable of learning low-level features like edges and lines and convert them to high-level features like shapes in the succeeding layers. Perceptron was the oldest trainable neural network with a single-layer architecture, that consisted of one input layer and one output layer. The novelty and trend of using CNNs in image recognition was after Krizhevsky et al [5] bagged the 2012 Imagenet Large Scale Visual Recognition Challenge (ILSVRC).There was only a 15% error rate in their model. Krizhevsky et al brought to attention relevant and important concepts that are used in CNNs today; concepts like Rectified Linear Unit (RELU) in CNNs, data augmentation and dropout. Thereafter, CNNs have gained importance and have become the most widely used model for image analysis.

1.3 LITERATURE SURVEY

Sr.No	Paper Title	Authors	Summary	Year
1.	Deep Learning Applications in Medical Image Analysis.	1.) Justin Ker, Department of Neurosurgery, National Neuroscience Institute, Singapore 2.)Lipo Wang , School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 3.) Jai Rao, Department of Neurosurgery, National Neuroscience Institute, Singapore 4.)Tchoyoson Lim, Department of Neuroradiology, National Neuroscience Institute, Singapore	This review introduces the machine learning algorithms as applied to medical image analysis, focusing on convolutional neural networks, and emphasizing clinical aspects of the field.We cover key research areas and applications of medical image classification, localization, detection, segmentation, and registration.	2017
2.	Breast Cancer Detection using Convolutional Neural Networks.	1.)Simon Hadush Nrea, Department of Computer Science and Engineering, Mekelle Institute of Technology - Mekelle University, Mekelle, Ethiopia. 2.)Yaecob Girmay Gezahegn, Mekelle Institute of Technology - Mekelle University,Mekelle, Ethiopia. 3.)Abiot Sinamo Boltena, Director-General, ICT Sector, FDRE Ministry of Innovation and Technology, Addis Ababa, Ethiopia.	Deep learning techniques are revolutionizing the field of medical image analysis and hence in this study, we proposed Convolutional Neural Networks (CNNs) for breast mass detection so as to minimize the overheads of manual analysis. CNN architecture is designed for the feature extraction stage and adapted both the Region Proposal Network (RPN) and Region of Interest (ROI) portion of the faster R-CNN for the automated breast mass abnormality detection.	2020
3.	Deep Learning in Medical Image Analysis.	1.Dinggang Shen, Department of Radiology, University of North Carolina at Chapel Hill, NC, USA, 27599. 2. Guorong Wu, Department of Radiology, University of North Carolina at Chapel Hill, NC, USA, 27599 3. Heung-Il Suk, Department of Brain and Cognitive Engineering, Korea University, Seoul, Republic of Korea, 02841	In this article, we introduce the fundamentals of deep learning methods; review their successes to image registration, anatomical/cell structures detection, tissue segmentation, computer-aided disease diagnosis or prognosis, and so on.	2017

Figure 1.2: Literature Survey

Chapter 2

MACHINE LEARNING AND DEEP LEARNING ARCHITECTURES

In this section, we will explore the various machine learning and deep learning architectures that aid in image analysis, detection, extraction and classification. Machine learning models are broadly classified into Supervised, Unsupervised, Semi-supervised and Reinforcement learning models. It is however, the first two models which are presently most relevant and applicable to medical image analysis. Hence, these two models are being focused upon in this review. Each of these models constitute a number of architectures that play a role in analyzing medical images.

2.1 GENERALIZED DEEP LEARNING ARCHITECTURE:

The general architecture of a deep neural network is shown in fig 2.1 . A deep neural network comprises an input layer, multiple hidden layers and an output layer. The neurons in each layer sums up the input data and applies the activation function on this input which gives the output. This output is then fed to the next layer. Adding more hidden layers enables us to deal with more complex features as they are instrumental in capturing non-linear relationships. The different types of deep learning algorithms which are in use are: Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN), Deep Neural Network(DNN), Deep Belief Network(DBN), Deep Autoencode(DA),Deep Boltzmann Machine(DBM), etc.

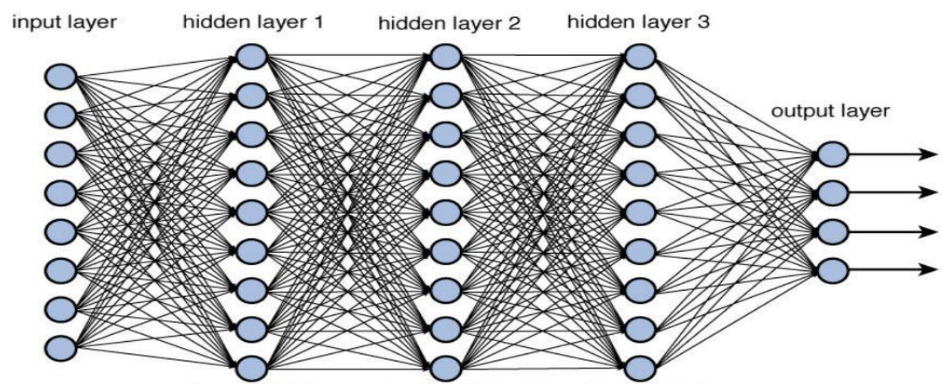


Figure 2.1: General architecture of Deep Neural Network

2.2 SUPERVISED LEARNING MODELS

2.2.1 Convolutional Neural Networks

CNN is by far the most popular choice of machine learning algorithm when it comes to image processing in general. Hence, they are also the most sought after algorithms for medical image analysis. The first CNN was created by Yann LeCun. CNN is a multi-layer neural network which is biologically inspired by the animal visual cortex. The reason why CNNs are preferred for medical image analysis is because of its ability to retain spatial information while filtering images. Spatial information is of utmost importance in medical practice, for instance, how bones are joint to muscles and what's the space between them, the boundary between normal and cancerous tissue, etc. CNNs can take as input both 2-D as well as 3-D images as input and process them, as both these types of images are critical to identify abnormalities. Therefore, CNNs are effective to analyze medical data as some methods like X-rays give 2-D while methods like MRI scans give 3-D images.

As illustrated in figure 2.2, CNN processes a raw input image and transforms through various layers viz. Convolutional Layers, Rectified Linear Unit (RELU) Layers and then the Pooling Layers. This is then fed into a fully connected layer. The Fully Connected Layer assigns scores or probabilities, and classifies the input image into the class with the highest probability.

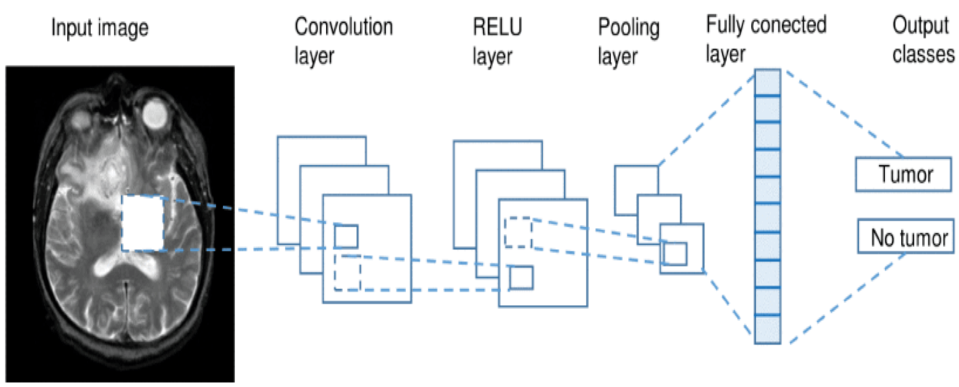


Figure 2.2: Feature extraction of the input MRI image of performed via the Convolution, RELU and pooling layers, before classification by the fully connected layer.

a. Convolution Layer

A convolution is defined as an operation taking place on two functions: one is the input image, i.e, the pixel values of the input images and the second function is the filter that we are going to apply. The filter is also called a kernel. Every filter is small spatially (along width and height), but extends through the full depth of the input volume. For example, a typical filter on the first layer might have size 5x5x3 (i.e. 5 pixels width and height, and 3 because images have depth 3, i.e, the color channels). Each of these functions can be represented as an array of numbers. The dot product of these two functions is what gives us our output. The filter is then moved to another section of the image which is decided by the stride length. This operation is performed repeatedly till the entire image has been covered. The final output is a *feature map* , also known as an *activation map*. It is called so because this is where the initial low-level features are detected.Now, we will have an entire set of filters in each layer, and each of them will produce a separate 2-dimensional activation map. These activation maps will be stacked along the depth dimension and produce the output volume. For example, if we were to give a photograph of a human face as input, after the first convolution layer, features like lines, edges and curves would be detected in the first feature map. These then go on to give higher features in the succeeding layers like eyes, nose, lips as these feature maps are the inputs for the next layer in the CNN architecture.

Convolution is characterized by three features that make it an efficient machine learning algorithm: Parameter Sharing, Equivariant spatial arrangement and Sparse

Connections. CNNs have sparse connections, where unlike other neural networks where every input neuron is connected to every output neuron in the networks, only a certain limited number of neurons are connected to the output layer. When dealing with high-dimensional inputs such as images, as we saw above it is impractical to connect neurons to all neurons in the previous volume. Instead, we will connect each neuron to only a local region of the input volume. The spatial extent of this connectivity is a hyper-parameter called the receptive field of the neuron(filter size). The extent of the connectivity along the depth axis is always equal to the depth of the input volume. It is essential to understand the asymmetry in how the spatial dimensions (width and height) and the depth dimension are treated: The connections are local in space (along width and height),but always full along the entire depth of the input volume. This enables gradual learning of meaningful features and also reduces the number of weights that are to be computed, thereby increasing the algorithm's efficiency. We can drastically reduce the number of parameters, by making one assumption: if one feature is useful to compute at some spatial position (x, y), then it should also be useful to compute at a different position $(x2, y2)$. Simply put, denoting a single 2-dimensional slice of depth as a depth slice. This is called parameter sharing and this is what enables CNNs to reduce memory requirements. This phenomenon is what enhances the quality of the invariant representation.

The convolution operation is defined by the $*$ symbol. An output (or feature map) $s(t)$ is defined below when input $I(t)$ is convolved with a kernel $K(a)$ [8]:

$$s(t) = (I * K)(t) \tag{2.1}$$

If t can only take integer values, the discretized convolution is given by[8]:

$$s(t) = \sum_{a} I(a) \cdot K\left(t - a\right). \tag{2.2}$$

A two dimension convolution operation with input I (m, n) and a kernel K (a, b) is defined as[8]:

$$s(t) = \sum_{a} \sum_{b} I\left(a, b\right) \cdot K\left(m - a, n - b\right). \tag{2.3}$$

By the commutative law, the kernel is flipped and the above is equivalent to[8]:

$$s(t) = \sum_{a} \sum_{b} I\left(m - a, n - b\right) \cdot K\left(a, b\right). \tag{2.4}$$

Neural networks implement the cross-correlation function, which is the same as convolution but without flipping the kernel[8].

$$s(t) = \sum_{a} \sum_{b} I\left(m + a, n + b\right) \cdot K\left(a, b\right). \tag{2.5}$$

b. Rectified Linear Unit (RELU) Layer

The Rectified Linear Unit is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value x it returns that value back. It is used to avoid the vanishing gradient problem. It can be written as:

$$f(x) = max(0, x). \tag{2.6}$$

There are many similar alternatives which also work well. The Leaky ReLU is one of the most well known. Activation functions like the sigmoid, tanh, Randomized RELUs and parametric RELUs are also prevalent but both practitioners and researchers have generally found insufficient benefit to justify using anything other than ReLU.

c. Pooling Layer

Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and calculations performed in the network, and thereby tackle the issue of overfitting. The Pooling Layer operates independently on every depth slice of the input and resizes it spatially using the MAX operation. The most commonly used form is a pooling layer with filters of size 2x2 applied with a stride of 2 for every depth slice in the input by 2 along both width and height, discarding 75% of the activations.

d. Fully Connected Layer

This is the final layer of CNN. Neurons in a fully connected layer have all connections to all activations in the preceding layer. There can be one or more than one fully connected layers depending on the amount of feature abstraction that is needed. The objective of a fully connected layer is to take the results of either the convolution, pooling or RELU layers and use them to classify the image into a label. The fully connected part of the CNN network goes through its own backpropagation process to determine the most accurate weights. Each neuron receives weights that prioritize the most appropriate label. Finally, the neurons "vote" on each of the labels, and the winner of that vote is the classification decision.For instance, on samples of histology glass slides, cancer cells possess a higher than usual DNA to cytoplasm ratio than regular cells. If features of DNA were predominantly detected from the previous layer, CNN would mostly predict the presence of cancer cells.

2.2.2 Transfer Learning with CNNs

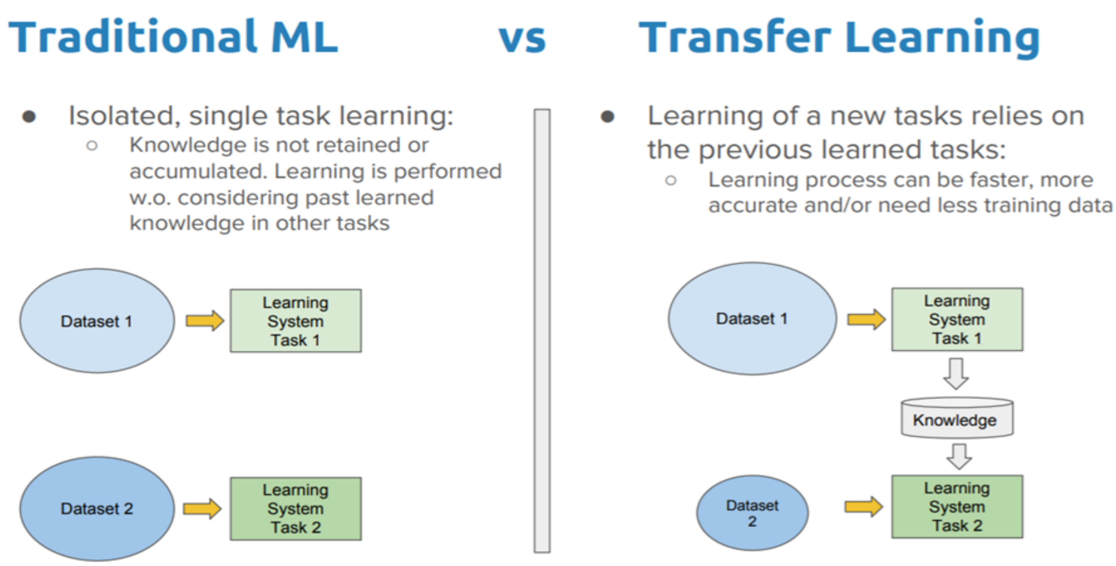


Figure 2.3: Traditional Machine Learning Vs. Transfer Learning

Although the medical data that is available are fairly labeled and structured, the amount of data required for the efficient training of the CNN is not very high. The basic premise of transfer learning is simple: take a model trained on a large dataset and transfer its knowledge to a smaller dataset. For object recognition with a CNN, we freeze the early convolutional layers of the network and only train the last few layers which make a prediction. The idea is the convolutional layers extract general, low-level features that are applicable across images — such as edges, patterns, gradients — and the later layers identify specific features within an image such as eyes, nose, etc. Transfer learning involves training a machine learning algorithm on a partially-related or un-related dataset, as well as a labelled training dataset, to circumvent the obstacle of insufficient training data.

2.2.3 Recurrent Neural Networks

Recurrent Neural Networks are widely known for their capacity to analyze and process sequential data like text analysis, language translations, text-prediction, speech-recognition, and also generation of captions for images[9]. In traditional neural network architectures, the inputs and outputs of each layer are independent of every other layer. But that is not the case with RNN. In an RNN, the output of a layer is fed as input to the next layer. This is then fed again into the same layer. This gives it the ability to retain certain pre-computed information, which serves as a "memory". Recurrent Neural Networks are rightfully called "recurrent", as they perform the same task over and over again for all elements belonging to a particular sequence, all of whose outputs rely on the previous computations in the sequence. In the domain of analyzing medical images, RNNs play the role of performing segmentation. Chen et al. [10] had performed a combination of RNN and CNN for segmenting neuronal as well as fungal patterns from an electron microscope. Stollenga et al. [11] performed segmentention on 3-D electron microscope pictures and also MRI scans.

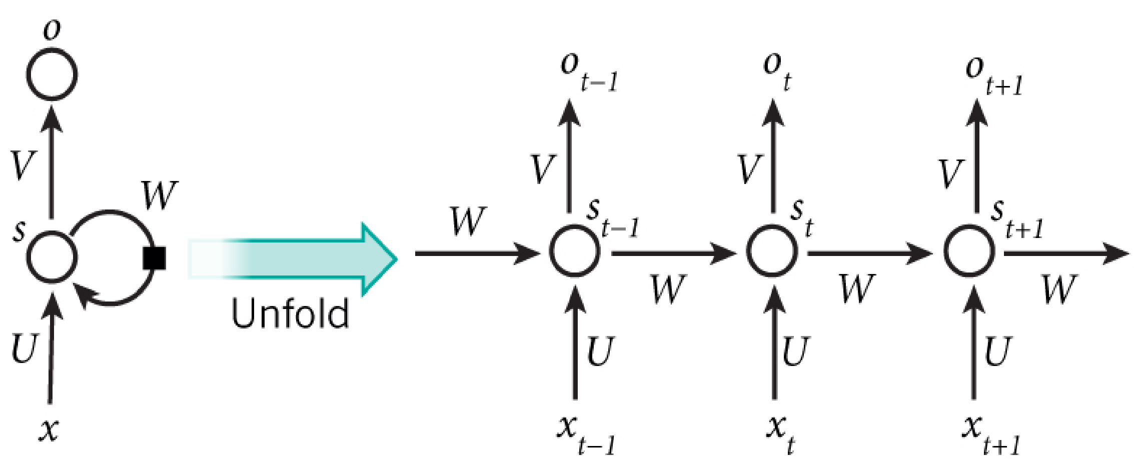


Figure 2.4: Recurrent Neural Network and its unfolding in computational time.

2.3 UNSUPERVISED LEARNING MODELS

2.3.1 Autoencoders

Autoencoder is an Unsupervised learning model. The primary goal of an autoencoder is to produce an output that is identical to the input fed into it. Autoencoders do not require training data, we can directly feed it with raw data and it will classify the data on it's own according to labels set by itself. Therefore, in a way, they are self-supervised. Autoencoders are composed of three important parts: Encoder, Coder and the Decoder. The encoder and decoder are separate fully connected layers each. The data is fed to the encoder. This data is then encoded and minimized. The decoder decodes this encoded data to reconstruct the output that looks identical to the input. Autoencoders also have a cost function which penalizes it when the provided input and the generated output varies from each other. Stacked Autoencoders (SAE) possess a symmetrical architecture in a way that the architecture of the encoder and decoder are like a mirror image of each other. This model is of great use in analysis of medical areas where there is inadequately and insufficiently labeled data.

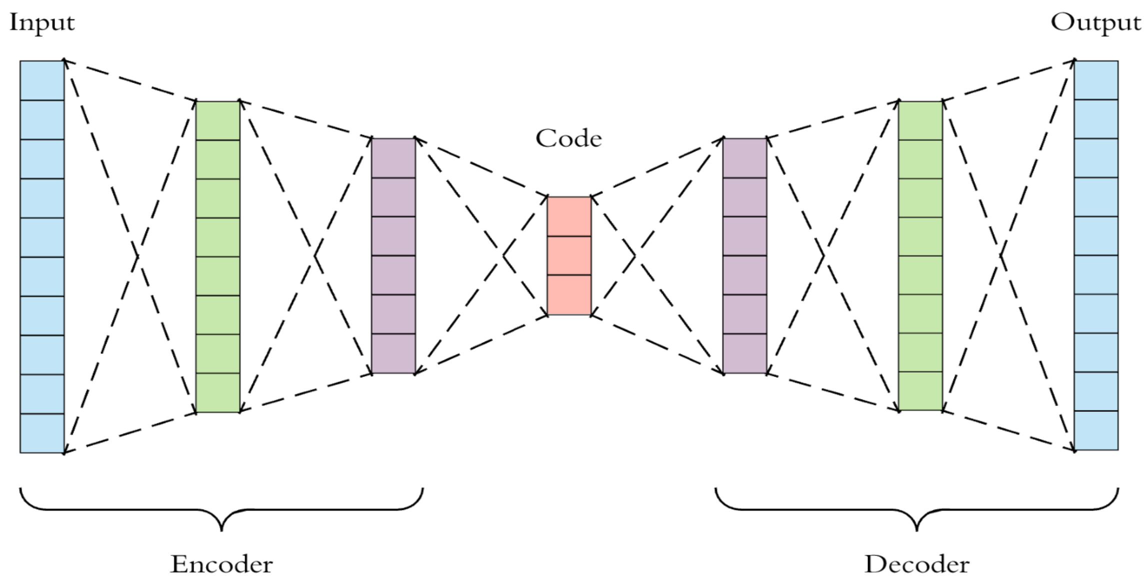


Figure 2.5: Autoencoder Visualization

2.3.2 Deep Belief Networks and Restricted Boltzmann Machines

Restricted Boltzmann Machine (RBM) is a unidirectional network that comprises visible and hidden layers. The number of neurons in each layer are the same. The neurons in one layer are connected to all other neurons in the other layer but none are connected within the same layer. Due to the symmetrical connectivity, the input data can be generated with the help of backward pass of input. RBMs' parameters can be trained with contrast divergence algorithms and stacked to form a deep architecture commonly referred to as the Deep Belief Network [13]. An inference that Hinton et al.[15] made was that these networks could be trained in a greedy method, one layer at a time. Therefore, the lower layers would be able to decipher low-level features and the succeeding higher layers would be able to recognize high-level features thereby imitating real-world like data hierarchical relationships. DBNs are generative in a sense that they 'generate' all the possible outcomes for a particular case. RBMs were applied to medical image analysis as reported by Khatami et al. [14] , who classified X-ray images using Deep Belief Networks into 5 distinct classes of anatomic areas.

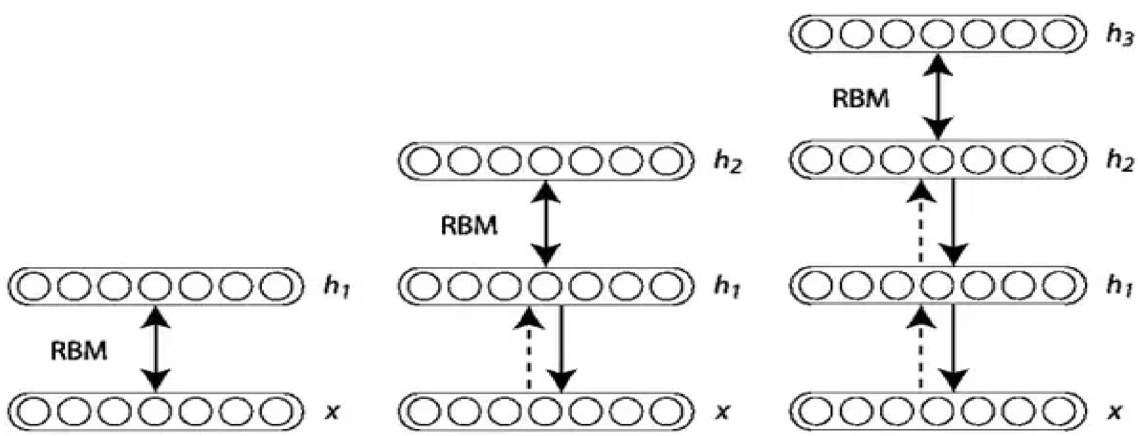


Figure 2.6: Deep Belief Networks and Restricted Boltzmann Machines.

2.3.3 Generative Adversarial Networks

Generative Adversarial Networks (GANs), as the name suggests, include two networks that are consistently competing against one another, hence the name 'adversarial'. They are used predominantly in image, video and voice generation. In the context of analyzing medical images, these networks compete against each other to generate synthetic medical images. One network is called the generator whose job is to generate artificial training images. The other competing network is named discriminator which determines whether the data generated by the generator are synthetic or real. The adversarials reach a final point when the discriminator can no longer tell the difference between real training images and artificial training images. GANs are comparatively new and one such application of GANs is in MRI segmentation.

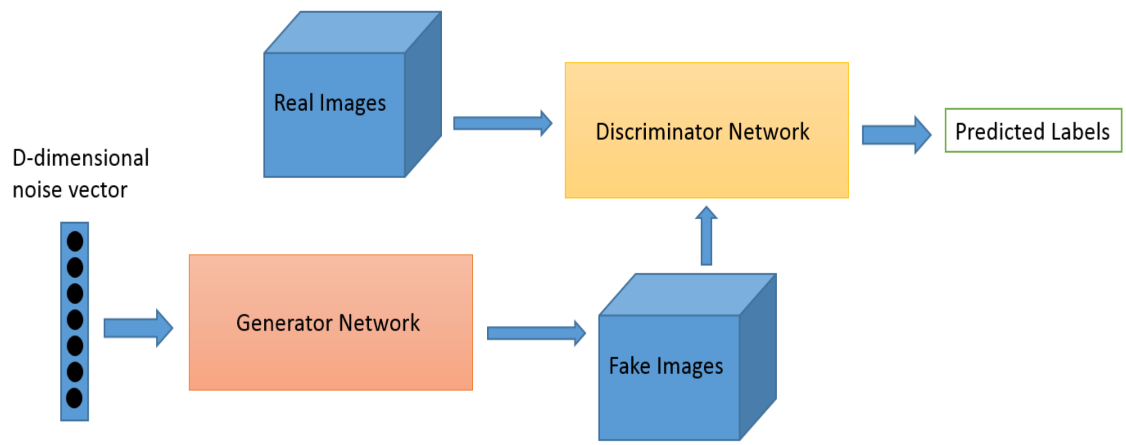


Figure 2.7: Generative Adversial Network.

Chapter 3

APPLICATIONS IN MEDICAL IMAGE ANALYSIS

The advancement in deep learning architectures like that of the CNNs draws attention to it's potential in the domain of computational analysis of medical data and how it can be applied to the images gathered by modalities like that of the CT, PET, MRI, X-ray, etc. CNNs perform the tasks of classification, localization, detection, segmentation and registration. In the context of machine learning independently, classification refers to the segregation of data into its appropriate labeled class; localization refers to the identification of a single object within the image with a bounding box; detection refers to the identification of multiple such objects within an image with bounding boxes around each of them; segmentation is responsible for identifying the target data and labeling it and lastly registration refers to fitting of images onto one another which includes 2D as well as 3D images.

With regards to a medical practitioner, it would be convenient to combine all these functionalities into a single working system. Therefore, from a medical perspective, **Classification** refers to determining if a disease is present or not, for example, does the CT scan of the chest of this patient contain a tumor? **Localization** refers to the presence of a normal body part, for example, where is the brain in the MRI image? **Detection** refers to the identification of all the abnormalities present in the image, for example, where are all the swollen lymph nodes in this X-ray image of the lungs? And lastly, **Segmentation** refers to the outlining the abnormality and studying its distance from the normal tissue thereby assessing whether the abnormality needs to be operated on or not.

3.1 CASE STUDY: BREAST CANCER DETECTION USING CNN

A study was conducted by Simon Hadush et al. [16] on breast cancer detection using CNNs and R-CNNs. The model detected abnormalities in the mammogram images and classified them as benign or malignant. The images were preprocessed with various filtering-layers: Gaussian, median & bilateral filters. This model had an accuracy rate of 91.86%, & a sensitivity of 94.67% in their prediction.

3.1.1 METHODOLOGY

DATASET

Dataset Source	Total patient cases (total MG images)	Total number of MG images with mass abnormality	Training	Validation	Testing
St. Gebriel Hospital	580(2224)	800	640	80	80
Grum Hospital	450(1684)	400	320	40	40
Korea Hospital	280(1024)	210	168	21	21
Betezatha Hospital	340(1270)	138	110	14	14
Kadisko Hospital	20(70)	40	32	4	4
Pioneer Diagnostic Center	20(68)	30	24	3	3

Figure 3.1: Dataset for Case Study.

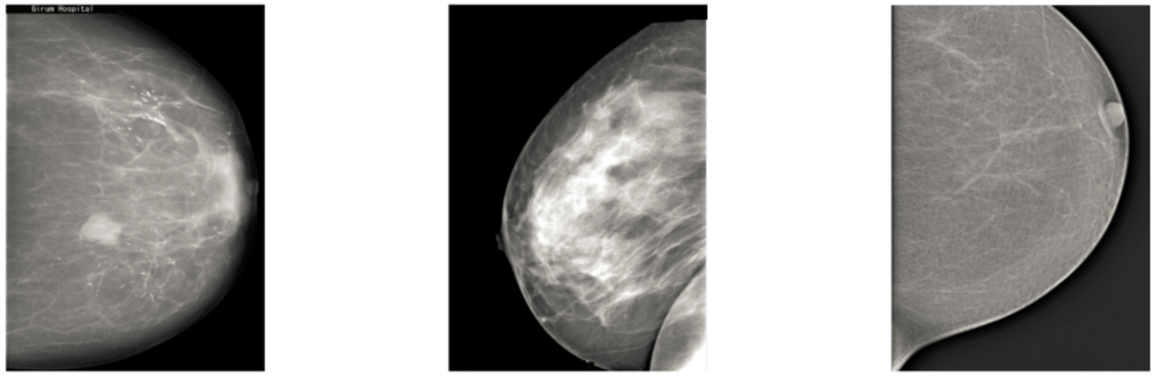
PROCEDURE

This model was implemented with the help Python and Keras and used Tensorflow as the backend.

1. **Data collection:** The experimental data that was to be used for this model was collected from various hospitals in Ethiopia as shown in figure 3.1.

2. **Preprocessing of Mammogram images:** The images of the mammograms were preprocessed in order to reduce the image-noise. Filters like the gaussian, median and bilateral filters were applied to achieve this.

3. **Training the Model:** Figure 3.3 shows our proposed model breast cancer detection. For training the model, a series of 5 convolution layers were used.



(a) (b) (c)

Figure 3.2: Sample of mammogram images during acquisition stage. The mammogram images are from different mammography x-ray sources: (a) from Girum Hospital, (b) from Pioneer Diagnostic Center, and (c) from St. Gebriel Hopital [16]

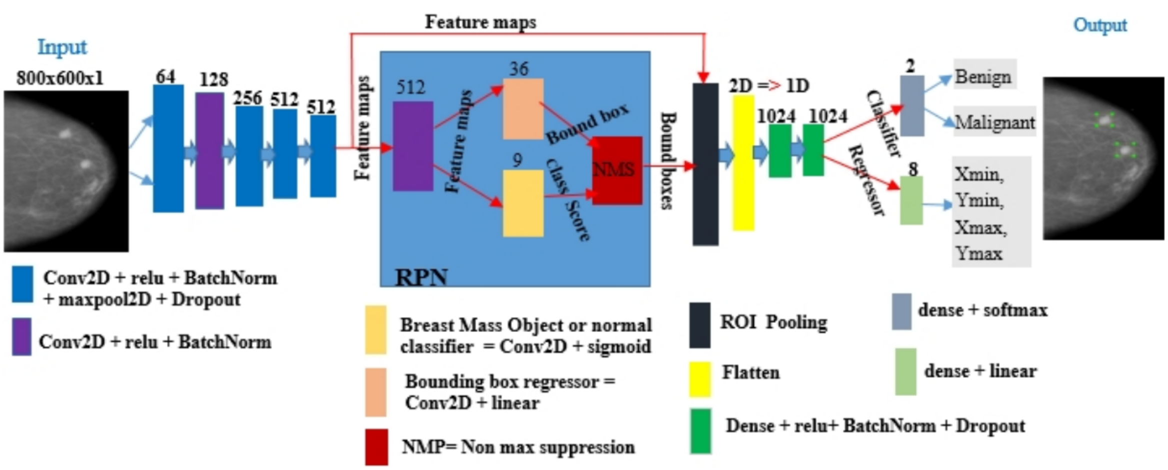


Figure 3.3: Proposed Model for Breast Cancer Detection.

Each convolutional layer was succeeded by a corresponding RELU, Batch-normalization, Max Pooling layers and Dropout. Convolution was performed with a kernel filter of (3,3), stride of (1,1) and same padding. The max pooling was performed with stride of (2,2) and kernel filter of (2,2) [16]. Fast R-CNNs were used for the detection of abnormalities.

3.2 RESULTS

This case study explored and performed the medical image analysis with a CNN-based approach. Using CNN, it detects, localizes and classifies the images into either benign or the malignant classes. The dataset was split for various needs as follows: 80% for training the model, 10% for validating it & 10% for testing the model. The image formats of DICOM were converted to .png during the pre-processing of images. Additionally, noise and other unwanted data were also removed using filters.

The classification result is summarized in table 3.1

Evaluation Criteria	Accuracy	Precision	Sensitivity	Specificity	AUC-ROC
Results(%)	91.86%	87.65 %	94.67%	89.69%	92.2%

Table 3.1: The proposed detection model performance: over all breast mass abnormality classification results in MG images [16]

Figures 3.4, 3.5, and 3.6, show the detected mass-abnormalities in the x-ray images. The detected abnormalities are highlighted using green bounding boxes. Each bounding box contains a class-name and a confidence-score.

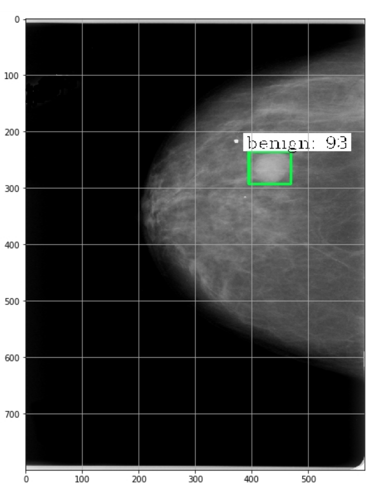


Figure 3.4: Benign

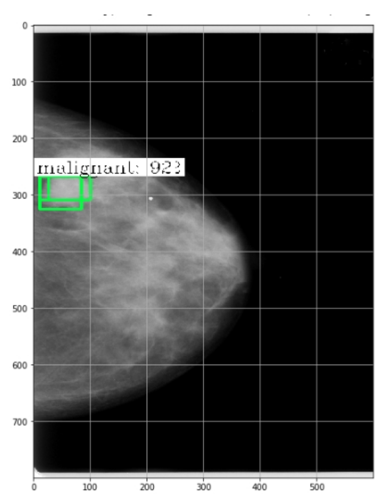


Figure 3.5: Malignant

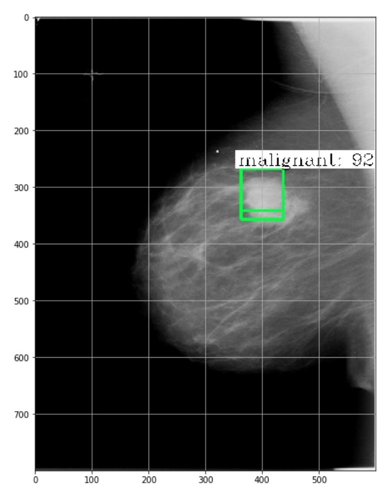


Figure 3.6: Malignant

This model is successful in preventing overfitting as well as internal covariance shift because of the batch-normalization layers and dropout in the RELU layers.

Chapter 4

CHALLENGES

4.1 Black Box and Its Acceptance by Health Professionals

One of the key issues of discussion with regards to deep learning algorithms and machine learning algorithms, in general, is the issue of black-boxes. The Black-box issue is pertinent as it implies that we don't know the inner workings of the stated algorithm. In layman's language, we feed the system with an input, we obtain the output, but we do not know how the model actually arrived at that output. Therefore, this could pose a challenge for using deep learning in medical image analysis as the implications of black-box could serve as a potential reason why healthcare experts wouldn't solely rely on these models alone, as there would be no one to take responsibility and accountability if something were to go wrong. Owing to the sensitivity of this issue, few of the hospitals might not yet be receptive to employ deep learning paradigms in their practice due to the black-box issue. Hence, unlocking the black-box is a research avenue that's being explored currently by researchers.

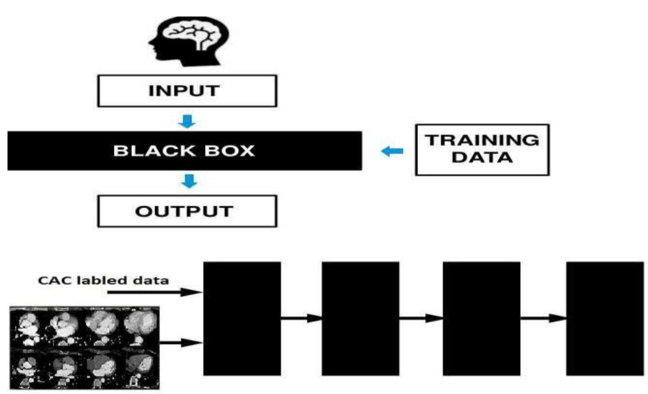


Figure 4.1: Black-Box

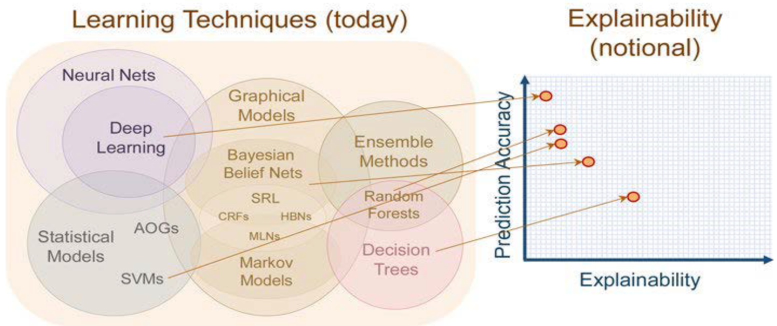


Figure 4.2: Explainability Vs. Prediction accuracy

4.2 Privacy And Legality

One of the primary areas of concern is the lack of available labeled "public" data. In the advent of the ever-increasing numbers of electronic medical health reports, there was a need to secure the patient's information as well. For this reason, many countries have put various medical data privacy laws in place, the likes of which are the United States of America, Canada, the United Kingdom, New-Zealand, and Netherlands. India presently doesn't have any such law. The Health Insurance Portability and Accountability Act (HIPAA) that was introduced by the United States is one such prominent medical data privacy law. This restriction of medical-data access can serve as a hindrance for training and testing deep learning models to ensure accuracy and efficiency. Although what's relieving is that it is possible to still accomplish our task with a smaller dataset due to the general similarity in the anatomy of all human beings. Yet, identification and analysis of rare-diseases could still be a problem. A possible solution to this would be the adoption of Generative models like the GAN which we discussed earlier. These models could be particularly beneficial for generating synthetic training data with the help of data augmentation, for rarely occurring diseases. Though, there might be a possible chance of over-fitting of data due to this. Another factor that comes into play is the general masses' acceptance of a non-human entity analyzing and studying their medical results, and making life-altering decisions for them. In its defense, Machine learning algorithms have outperformed humans on countless occasions especially in image-recognition. And hence, it is more than likely that it will have the same accuracy and credibility in analyzing medical images as well.

Chapter 5

Future Scope

The healthcare domain is one that has immense scope for research and applications of emerging deep learning and machine learning models for its advancement. Deep learning has a promising future of further revolutionizing the medical sector owing to the big data that's being generated on a day-to-day basis. A few of the interesting applications that are possible in the near future are discussed below:

One such promising application of deep learning was had been reported by Nie et al. [17] . In his report, he proposed that GAN's could be used to produce CT scans from already taken MRI images of patients. This is highly beneficial as this prevents the patient from having to undergo the hassle of being exposed to the ionizing radiation of CT scans altogether. This is also cost-effective and a safer option for people. Nie et al. also reported that the image-resolution of medical images could be improved so that they could be studied better.

Coudray et al. [18] in his study, showed how histopathological images were used to study and classify the subtypes of lung cancer in order to predict probable genetic mutations. This model outperformed a human pathologist. Knowing the possible genetic mutations help the medical practitioners to foretell the chances and probability of the patient's survival and guide the patient to make the right choice of therapy. Their model had an AUC(Area Under Curve) score of 0.73-0.86 for the prediction of mutated genetics.

The aforementioned examples reiterate and re-establish the influence, wide-ranging applications and the rising potential of incorporating deep learning in medical practices to improve and advance the health sector.

Chapter 6

CONCLUSION

The advent of deep learning in the field of medicine has remarkably changed the way healthcare sectors function, by assisting them with tough, life-or-death like situations. We have only begun to reap the benefits of machine learning. Numerous other breakthroughs and advancements are yet to be made. This report has also highlighted the possible limitations that can be faced like that of the black-box characteristics of deep learning models and also the limited public medical data that is available. This issue can be resolved with the collaboration of various medical professionals, hospital providers, machine learning researchers and also the law-makers so that appropriate laws can be put in place regarding a patient's EHR and how it can be legally and safely used for training, validating and testing deep models. Deep learning methodologies have achieved state-of-the-art gains over other medical applications both in terms of patient safety as well as in assisting and making the jobs of medical professionals easier. This is a huge achievement.

Bibliography

[1] Canada Health Infoway. Annual report 2014-2015: the path of progress. Toronto: Canada Health Infoway; 2015. [Google Scholar]

[2] National Health Service [Internet] London: National Health Service; c2016. [cited at 2016 Oct 22]. Available from: http://digital.nhs.uk. [Google Scholar]

[3] German Federal Ministry of Health. The electronic health card [Internet] Bonn: Federal Ministry of Health; c2016. [cited at 2016 Oct 22]. Available from: http://www.bmg.bund.de/en/health/the-electronic-health-card.html. [Google Scholar]

[4] New Zealand National Health IT Board [Internet] Wellington, New Zealand: Ministry of Health; c2016. [cited at 2016 Oct 22]. Available from: http://www.healthitboard.health.govt.nz. [Google Scholar]

[5] A. Krizhevsky, I. Sutskever, G. E. Hinton, "ImageNet classification with deep convolutional neural networks", Proc. Adv. Neural Inf. Process. Syst., pp. 1097-1105, 2012.

[6] Osmany, Nooshin. (2016). Machine Learning in Biomedical Applications: Case Study Breast Cancer. 10.13140/RG.2.2.19707.52005.

[7] G. Litjens et al., A survey on deep learning in medical image analysis, Jun. 2017, [online] Available: https://arxiv.org/abs/1702.05747.

[8] J. Ker, L. Wang, J. Rao and T. Lim, "Deep Learning Applications in Medical Image Analysis," in IEEE Access, vol. 6, pp. 9375-9389, 2018.

[9] I. Sutskever, J. Martens, G. E. Hinton, "Generating text with recurrent neural networks", Proc. 28th Int. Conf. Mach. Learn. (ICML), pp. 1017-1024, 2011.

[10] J. Chen, L. Yang, Y. Zhang, M. Alber, D. Z. Chen, ”Combining fully convolutional and recurrent neural networks for 3D biomedical image segmentation”, Proc. Adv. Neural Inf. Process. Syst., pp. 3036-3044, 2016.

[11] M. F. Stollenga, W. Byeon, M. Liwicki, J. Schmidhuber, ”Parallel multi-dimensional LSTM with application to fast biomedical volumetric image segmentation”, Proc. Adv. Neural Inf. Process. Syst., pp. 2998-3006, 2015.

[12] Shen D, Wu G, Suk HI. Deep Learning in Medical Image Analysis. Annu Rev Biomed Eng. 2017;19:221–248. doi:10.1146/annurev-bioeng-071516-044442

[13] M. A. Carreira-Perpinan, G. E. Hinton, ”On contrastive divergence learning”, Proc. Aistats, vol. 10, pp. 33-40, 2005.

[14] A. Khatami, A. Khosravi, T. Nguyen, C. P. Lim, S. Nahavandi, ”Medical image analysis using wavelet transform and deep belief networks”, Expert Syst. Appl., vol. 85, pp. 190-198, Nov. 2017.

[15] Y. Bengio, P. Lamblin, D. Popovici, H. Larochelle, ”Greedy layer-wise training of deep networks”, Proc. Adv. Neural Inf. Process. Syst., pp. 153-160, 2007.

[16] https://arxiv.org/abs/2003.07911

[17] D. Nie et al., ”Medical image synthesis with context-aware generative adversarial networks”, Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., pp. 417-425, 2017.

[18] N. Coudray, A. L. Moreira, T. Sakellaropoulos, D. Fenyo, N. Razavian, A. Tsirigos, ”Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning”, bioRxiv, pp. 197574, 2017, [online] Available: https://doi.org/10.1101/197574.