A STUDY DEPICTING THE ADVENT OF ARTIFICIAL INTELLIGENCE IN HEALTH CARE

J.Paruvathavardhini[1], S.Menaga[2], N.Gomathi[3], S.Karthikkumar[4], S.Brindha[5]

[1] Electronics & Communication Engg, Jai Shriram Engineering College, Tiruppur, India

[2] Electronics & Communication Engg, Jai Shriram Engineering College, Tiruppur, India

[3] Computer science Engg, Jai Shriram Engineering College, Tiruppur, India

[4] Electrical and Electronics Engg, Jai Shriram Engineering College, Tiruppur, India

[5]Electronics and Communication Engg, Nandha Engineering college, Erode, India

ORCiD: 0000-0003-3654-7182[1], 0000-0001-9798-7507[2], 0000-0002-2001-7614[3], 0000-0003-1066-9851[4]

Abstract:* Artificial intelligence in Healthcare is revolutionizing the medical industry by providing a helping hand. AI in healthcare is changing the game with its applications in decision support, object detection, image analysis, solving complex problems, and patient triage. This study discusses how AI technologies such as deep learning, neural networks, and machine learning help in clinical decision making and diagnosing process. It also includes how a complex algorithm is developed using the deep learning and neural networks in making clinical-decisions to be precise and how easily it handles the high dimensional medical data. Similarly, it shows how Machine learning is used in automatic analysis of medical images and identifying diseases at its earlier stage. Various diagnostic studies like radiology, clinical observations like MRI, EEG, ECG, selection of antibiotics, orthopedics, retinal analysis, etc. These studies also illustrate cognitive technology and Nuance which is used to maintain the medical records and perform power diagnosis. The important factor that is required before any diagnosis is the patient history and about the medication what they are undergoing, this can be achieved by maintaining the electronic records (ie)EHR in the cloud using IoT, which can be retrieved at anytime. EHRs play a major role in identification and treatment of cancer and this data can be updated in the learning process of AI as they are updated each time. This study also depicts how smart devices can be used to alert the patient regarding their abnormality. It also discusses about how wearable sensors play a significant role in monitoring the post surgery patients and avoid complications and readmission. It is concluded that AI plays major in all the areas like detection, diagnosis, treatment and also further follow ups.

***Keywords:* Artificial intelligence, deep learning, neural networks, machine learning, nuance, cognitive technology, clinical decision making**

INTRODUCTION

Artificial intelligence plays a major role in our day to day life. AI is the development of a computer system that is capable of performing tasks that normally require human intelligence such as decision-making, performing the computation, solving complex problems, and so on. Since the introduction of AI in the 1950’s it is influencing in various domains like marketing, financial, gaming industries, and musical arts. However, the largest footprint of AI is in the field of healthcare. AI is estimated to contribute over $15.7 trillion to the world economy by the year 2030 and the greatest impact of AI will be in the field of healthcare. [1] The technique of Artificial intelligence have sent tremendous waves across medical services, yet fuelling an energetic conversation of about AI specialists will in the long run supplant human doctors later on. We accept that human doctors won't be supplanted by machines soon, yet AI could help doctors to settle on better clinical choices or even supplant human decision in certain practical territories of healthcare. The expanding accessibility of medical care information and quick advancement of huge information logical strategies has made conceivable the ongoing fruitful utilizations of AI in medical services. Guided by important clinical inquiries, incredible AI strategies can open clinically significant data covered up in the monstrous measure of information, which thus can help in clinical decision making. [2-4]

In this article, we review the present status of AI in medical services. The survey can be made on the four aspects relevant to medical challenges:

Technologies combining with AI to provide solution to medical issues.

Analyses of medical data through AI systems.

Different mechanisms in AI systems to identify the various disease and make medical meaningful results

Assist doctors in tackling the diseases

AI DEVICES:

MACHINE LEARNING:

Machine learning is a subset of AI which makes machine to learn automatically and improve from experience without being explicitly programme. Specifically feed the Electronic Health care datas (MRI scan, X-Ray,Blood test etc.) were feeding into the machine.It interprets process and analyze the data by using machine learning algorithm, then it understanding the problems and predict an outcome based on the data to solve the problem.[2,5]

DEEP LEARNING:

Deep learning is a collection of statistical machine learning techniques used to learn the feature hierarchies based on the concept of Neural Networks. Deep learning is an more advanced concept of Machine Learning that uses Neural Networks offering the ability to solve the complex problems for higher dimensional data and to extract the features. The structure of Neural Networks is like human brains in which neurons are interconnected with one another to process the data. Each layer may be assigned a specific portion of transformation of raw data might transverse the layers multiple times to refine and optimize the ultimate output. Deep Learning used to identify the abnormalities in medical records, clustering patients etc. Deep learning can gauge the accuracy of its answers on its own due to the nature of multi-layered function. [6, 7]

For any type disease the doctors will require a patient history for clinical decision, and this can be extracted from Electronic Health Records (EHR). This stored information about a patient must be in a sequence (ie) in a temporal context.

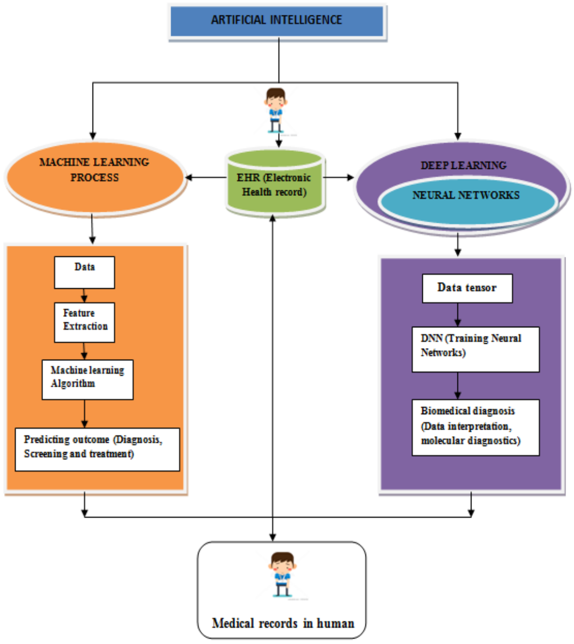

Fig.1.AI in Healthcare system

It is very difficult to maintain this EHR because of its domain specific nature, lack of structure of context and writing quality. So we need a system to convert highly detailed information of the patients digitally and store it in to a EHR especially for the oncology department. A smart system must be able to extract the concepts, date expressions, temporal relations and ordering noted and translate it to the requirement of an EHR. M. Najafabadipour, et al.,[8] developed a new technique called Natural Language Processing (NLP) is introduced to extract the above mentioned elements written in any language also in Spanish by using rule-based methods.

Basically there are three challenges faced in extracting the text, they are,

Challenge 1- The physicians would have noted the data in the textual, like pattern extraction and better understanding of thedisease evolution, toxicity rates and treatment response and outcomes. The stage code of the cancer classification is really a challenging task.

Challenge 2- Liking the medical events with date expressions is an other hectic process, as the event will be in text and the date will be in the different pattern. Sometimes the patient's data may be stored twice in same date, that should also be evaluated before recording the data.

Challenge 3- Storing and extracting the history in an orderly manner with temporal relation is an other challenge.

So in order to provide a novel NLP framework, a set of annotators developed by Unstructured Information Management Framework (UIMA) is used along with temporal identification process facilitated with tokenization and section recognizer of C-liKES(a text mining system, developed to ingest informationwritten in Spanish free-texts format). Especially lung cancer diagnosis concepts, tumor stage codes and dateexpressions is annotated in this paper.

Methods used:

The frame work consists of two stages:

1)The Temporal Reasoning System, which links medicalevents to their corresponding date expressions in the EHR; and

2) TheTimeline Constructor, which generates the patient’s medical timeline.

The process of NLP framework is as follows:

The aforementioned elements of a lung cancer patient’s record will be given in the XMI file format.

The temporal reasoning system will read and identify the temporal relations between the date, stage code etc with the help of Universal Dependency Pipe(UDPipe) by building the dependency parse tree relations and store it in a MySQL database.

Note:To identify the stage code of lung cancer from clinical data, stage annotator and TNM annotator is used based on UIMA framework.

The temporal relation identification is used to create relation between the textual data, differentiating the nouns, verbs, predicates in the sentences. It also checks the dates of the record if it is found two times and also the words used in the sentencesto find whether is is noted at the same instance or at different time.

Timeline constructor is used to omit the unnecessary information of the patient history, timeline it and store it in a database. It evaluates the semantic similarity and metric medical event(ie) date expressions and stage code of the tumor.

Thus the framework was evaluated using the dataset containing 989 patients record which corresponds to 296,003 EHRs, average of 300EHRs per patient. Thus the framework is validated after various steps of evaluation processes and achieved a precision of 1.000 within a confidence interval of (0.952,1.00), recall of 0.872• }0.089 and F1 of 0.932

.

L Macías-García, et al., [9] has proposed a paper to characterize the recurrence of the breast cancer from genes and to diagnose the survival rate of the patients from the datasets of DNA methylation using the autoencoders(AE). DNA methylation is a biological process by which methyl groups are added to the DNA molecule. This process can change the activity of a DNA segment without changing the sequence. An autoencoder is a type of artificial neural network with symmetric structure in which the input can be encoded in to the middle layer and its version can be decoded from the output layer. Thus after methylation, the databases are characterized to have high dimensionality with some cases, this is called as High Dimension Low Sample Size (HDLSS) databases which are well-known for issues regarding feature selection. So in-order to reduce this risk autoencoder takes advantage of their capacity to reduce the dimensionality while maintaining prediction accuracy.

A comparative study is also proposed based on this along with an enriched literature analysis to give the survival status based on the patient’s condition. The datasets of the patients were collected from The Cancer Genome Atlas (TCGA) data portal and methylation status were collected from the CpG (Clinical practice guidelines) statements. Classification is actually done using four different methods like decision trees (DecisionTreeClassifier GradientBoostingClassifier, and RandomForestClassi_er implementations in), support vector machines (SVC and NuSVC), meta-learning classifiers (AdaBoost classifiers and GradientBoosting classifiers), Bayesian classifiers (GaussianNB) and the k-nearest neighbours algorithm (KNearestNeighbors) as lazy/instance-based classifiers and the five-fold cross validation procedure is used to obtain accuracy. The heavily weighted genes related with the recurrence of breast cancer generated using AE is classified into five groups confirmed-recurrence biomarkers, probable-recurrence biomarkers, obesity-related biomarkers, chemotherapeutic inhibitors and probable pesticide exposure indicator. Thus the relevant underlying genes were discovered by the enrichment analysis based on the previous biological parameters.

Simon Meyer Lauritsen,et al., [10] has discussed that Sepsis is a serious life threatening condition in a patient’s body caused in reaction to an infection. This has to be predicted at the earliest stage to prevent the patient from death. The mortality rate is increasing year by year because of this sepsis problem. The older studies built machine learning models from EHR to diagnose this problem, but that was limited up to intensive care unit level only because the out patients were not frequently monitored. And moreover AROC curves were used to evaluate the prevalence of sepsis in a patient. But here in this paper , a scalable deep learning by training the neural networks based on the heterogeneous data collected from in and out of the hospital. The data for this project was collected from “CROSS-TRACKS”. The full data set collection is called as the vital data, in which non-symptomatic data are removed. In this list also the data set was divided into two parts, sepsis positive and sepsis negative cases to train the neural network. So a patient will be predicted with the symptom of sepsis if the presence of two or more Systemic Inflammatory Response Syndrome (SIRS) criteria paired with a suspicion of infection. The SIRS criteria are defined as:

• heart rate >90 beats/min
• body temperature >38°C or <36°C
• respiratory rate >20 breaths/min or PaCO2 (alveolar carbon dioxide tension) <32mmHg
• white cell count >12×109 cells/L or <4 ×109 cells/L

The raw data collected will be transformed by a two-step vectorization of individual events. Three types of model is used in this data processing namely

1) Gradient boosting(GB-Vital)- a classical epidemiological approach, where the modelincludesa small group of selected and clinically well-founded features.

2) Multilayer perceptron- a more data-driven approach, where all the available data is used in a slightly aggregated form to train a non-sequential neural network

3) CNN-LSTM- a data-driven approach, where the available data is used in its sequenced form for the training of a sequential neural network.

The old data were taken from multiple Danish hospitals for over seven years and the above mentioned models were used to assess the accuracy and found that major of the patient have not been intervened with any antibiotics or blood culture. From this we conclude that, for exact precision the patient’s records must be evaluated from the day they enter into the hospital. The model should be evaluated by discriminating the decisions given by the different models which gives the exact prediction even from false negative and false positive.Thus an accurate deep learning process is implemented for early detection of sepsis, with a precision point ranging from AUROC 0.856 (3 h before sepsis onset) to AUROC 0.756 (24 hbefore sepsis onset). Hence the model developed may help the clinical physicians to predict the sepsis at the earliest stage whether the patients were intervened with antibiotics or blood culture tests or may not have been.

Farhad Ahamed, et al., [11] has proposed a paper on how to apply IoT and machine learning together to improve personalized healthcare (PH)of a patient. They take the example of the personalized diabetic care in which the patient’s sugar will be checked periodically and their diet will instructed asd per the range of their sugar level. It will be monitored continuously and with the help of IoT, the data will be stored in the cloud for further reference. When the post surgery patients are monitored with the help of PH continuously, the re-admission can be avoided upto 40% and unnecessary expenditure can be avoided to a greater extent. IoT and

ML together concentrates in three areas like 1) Diagnostic care 2) Assistive care 3) Monitoring and alarming which provides a greater support to the remote patients. The ML is used to train the device

(smart phone or gadget) that is used to assist the patient. The wearable sensors for different monitoring follows the patient condition and updates the data to the gadget which in turn provides the appropriate diagnostic care to the patient. IoT plays a major role here by updating the data in the cloud and at the same time the updated data will also be taken as a further learning and the device will provide the medical suggestions to the patient. When the monitored condition is found to be critical it also instructs the patient or their relative about it immediately. They also summarize that when the technology is advanced, the risk also goes high, like privacy problem of hacking the data, etc. Further investigation has to be done on this to improve security regarding privacy.

Bhagyashree Mohanta, et al., [12] has discussed about the disadvantages of the 4G technology in healthcare like flawless data transmission with no data loss, free traffic transmission channels, cost, sometimes the system requires human intervention in M2M communication or in D2D(Device to Device) communication, problem in data retrieval. Implementation of 5G communication will support in improving Smart Healthcare which starts from patient's OPD visit to operation extending up to post operation care and remote healthcare. The significant role of 5G communication is to provide high speed data transmission, improve coverage area, high capacity to control network traffic, highly responsive, low cost and the ability to connect a lot more devices at once. IoT is used for patient monitoring with the help of wearable sensors and store the data to the cloud and further process it and send the report to the doctor or the relatives. As an advancement, the AI along with IoT can be used to analyse the CT scan or X-ray reports and diagnose the diseases related to genes and genomes more effectively which can save the patient's life. Also, this helps to avoid the readmission and unnecessary visit to the hospital and diseases due to hospital acquired infections (HAIs). The smart devices gives suggestions to the patients about any abnormality observed, if in case of severity, it suggests them to visit the doctor. The smart blood bank simplifies the search for a donor in which all the data regarding the donor and the required blood group, so it can be easily accessible. The Smart Waste Management in Healthcare 5.0 Scenario is a concept to create a sustainable environment to prevent the spreading of the contaminated diseases. The role of AI us major as it creates a new revolution in the field of healthcare. Machine thinking is more advanced and precise than the human in case of diagnosis.

Yue Wu, et al., [13] has discussed about the antibiotic selection for treating children with osteomyelitis (OM), a serious bacterial infection seems to be a challenge to the pediatricians as the culture test will be sometimes falsely negative and at times falsely positive. The bacterias that causes OM are Staphylococcus, Pseudomonas and Enterobacteriaceae which spread to the bone through the bloodstream because of some infectious disease or wound from recent surgery or may be due to an injection in and around the bone. When the physician chooses the dosage too narrow will end at failure of the treatment in case of the result being falsely negative, if he chooses the dosage too broad will end at increasing toxicity or antibiotic resistance.

So Bayesian network is used to develop a model that forms a complex relationship between the obtained culture test result, the unobserved infecting pathogens, clinical and demographic variables and further integrates these data with most analytic expert knowledge under a causal interference framework. This BN models helps the clinical experts to aptly choose the dosage of the antibiotic. The percentage of prediction of causative pathogens prevalence in children with OM using this BN model was precise up to 57% for Stappylococcus, 17% for Streptococcus, 27% for bacterial pathogens that are not culturable using normal methods.

Log loss cross-validation suggests that the BN mode prediction is robust and the dosage suggested is also approved as optimal by the experts in 81-98% of 81 cases sampled from the cohort(An- ancient military unit). When the outcomes of the test results from different specimens using this model were plotted using AUC, the values were around 0.68-0.77.

In today's urgent world, many are aware but most of them are not aware of the fatal condition of heart attack or irregular cardiac arrhythmia (an irregular heartbeat condition) which exists from newborns to old person. ECG(ElectroCardioGram) is one of the method to record the heart beat of humans. From this recorded signal clinical physicians will predict the condition of a person's cardiac arrhythmia. So this analysis has to be done very precisely in order to prevent sudden deaths. Though the researchers has derived many algorithms, still no proper solution is derived to assist the real time and clinical environments. A clear and extensive study has been performed by Arun Kumar Sangaiah, et al., [14] to remove the noise present, feature extraction and classification of ECG signals from the records obtained from the MIT BIH arrhythmia database represented in Fig1. The frequency of the ECG signal ranges from 0.5-100Hz, but the useful information is available between 0.5-40Hz, so the presence of noise will totally mask the important morphology of the signal and produces inaccurate results. The most important types of noises present in an ECG signal are baseline wander (BW), power line interference (PLI), and electromyography (EMG) or muscle artifacts, motion artifacts, electrosurgical and instrumental noise. Here, in this paper an IIR elliptic high pass filter of order 3 and with a cut-off frequency of 0.5 Hz is proposed to obtain better performance with less computation time and low memory space requirement.

The features of the ECG signal is extracted using discrete wavelet transform, there are five types of ECG beats namely, Normal (N), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Premature Ventricular Contraction (PVC) and Atrial Premature Contraction (APC) represented in Fig2. The mother wavelet selection and the number of the decomposition levels is the significant step in the processing of the ECG signal. The db8 is chosen as the mother wavelet and the features are extracted up to six levels. The filter bank chosen includes high pass filter for output details and low pass filter for input approximations.

Five types of arrhythmia is classified in this work by an improved hidden Markov model which is obtained by fusing wavelet transform and hidden Markov model. So the efficiency of the developed model is measured in terms of sensitivity, positive predictive value, and detection error rate.

This work also includes Internet of Medical Things (IoMT) which combines open-source Internet of Things (IoT) platform, ThingSpeak(Application Peripheral Interface for storing, processing and retrieving data from the cloud using HyperText Transfer Protocol (HTTP) protocol over the Internet or through a Local Area Network) to analyze and visualize live

data streams in the cloud. And this predicted information will be conveyed to the clinical physicians. The proposed HMM classifier has an average accuracy of 99.8% in classifying the samples into five types of arrhythmia. The sensitivity and positive predictive value of the proposed model is 99.8% and 100%.

David Calhas, et al., [15] has analysed about the recording of brain activities using the Electroencephalogram(EEG) creates many opportunities to study and diagnose many neurological disorders. Schizophrenia is a serious mental disorder in which people interpret reality abnormally. Schizophrenia may result in some combination of hallucinations, delusions, and extremely disordered thinking and behavior that impairs daily functioning, and can be disabling. People with schizophrenia require lifelong treatment. Till now there is no proper algorithm to extract neuro-plasticity relayed features from resting stage EEG data with deep learning. So here we propose a Siamese neural network to learn the selective features from pair-wise combinations of observations. Also this should be achieved with limited number of datasets. There are two main steps,

1) Feature extraction- A EEG has multivariate signals in different time, so there is a possibility of giving false positive and false negative results. The signals recorded from cerebral cortex is a univariate time series which is recorded using EEG has to be decomposed using discrete fourier transform. This is called spectral analysis. A sliding window of raw data is allowed to run over a this spectral series to obtain the relevant changes that is noticed in the brain activity and this is called spectral imaging.

2) Classification-

Step 1- the internal representationsobtained from the SNN architecture model are extracted

after training.

Step 2, a classification task is performed using theseextracted features.

After this hyperparameter classification is done using Baysesian optimization. Thus this developed method increases the diagnosis of this Schizophrenia by 20-30% without hampering sensitivity or specificity.

Wan-Jung Chang, et al., [16] have developed a wearable medicine recognition system which helps the visually impaired person. There are totally about 285 million blind people, in that 140 million people are above 50 years who suffer from many chronic illness and are under medication. Visually impaired have very less chances of life support in case of irrational drug usage. There are many works that was proposed in association with various food and drug administration of USA for pill identification. The proposed system has four components which includes a pair of wearable smart glasses, a waist mounted drug pills recognition device, a mobile device application (app), and a cloud-based management platform.

The waist mounted device will give a voice message that to remind the person to take the pill, the wearable glass will take a picture of the pill from the person's hand and send it to the waist mounted pill recognition system. It will perform a deep learning based on image recognition by usingfaster region-based convolution neural network (Faster R-CNN) and Google Inception V3. After the recognition of the pill, the device ensures and gives a voice message if he can take the pill or reject it. The device also holds power-efficient embedded AI computing module (NVidia Jetson TX2 adopted), amobile battery-powered source, a 15W dual bridge amplifier(TDA7297 adopted), and a speaker. The drug pill recognition was accurate up to 90%.

Ali Kaplan, et al.,[17] reviewed of people are suffering from different types of cancers because of being exposed to unwanted radiations, food habits, medications, etc. in that skin cancer is also a type which starts with a sign of a mole. Now a days the clinical physicians are expecting a support fromclinical decision support systems (CDSS), which can offer specific patient assessments or recommendations to physicians. This can reduce the risk of many false positive and false negative identifications in case of this skin cancer. As mentioned earlier it starts as a mole and develops as s melanoma which is a serious form of skin cancer that begins in cells known as melanocytes. While it is less common than basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), melanoma is more dangerous because of its ability to spread to other organs more rapidly if it is not treated at an early stage. So a system model has been proposed in order to precisely differentiate and identify the spread of a melanoma from normal mole. A pre-trained networks (ie.VGG-16) based on deep learning technique is been used to predict the melanoma from dermoscopic images (Dermoscopy is a method to examine the pigmented skin lesion).

Note: VGG-16 (Visual Geometry Group) is a convolution neural net (CNN) architecture one of the excellent vision model architecture till date.

Le Nguyen, et al., [18] discussed about the advanced technology of AI in healthcare and also models the virtual nurse using AI with Blockchain technology to assist both the doctor and patients.

Authors demonstrate three main models of the AI Mobile AppModel 1(Appointment Booking) while booking an appointment, AI App starts communicating with the user by asking about the condition of the case either emergency or non-emergency. In the emergency case condition, an existing list of doctors will be revealed to the patients; otherwise, a patient can book an appointment by choosing the location and available time of expert doctors in the field that the patients are having problems like cancer surgery, eye surgery, etc. Model 2 (Test result analyzing) is used to analyze the patient records by scanning the tests which were taken by the patients before surgery like MRI, blood test, etc. This test report will be analyzed by AI's image library. If the patient using the app for the first time, the output is a doctor's comment. If the case is already existing, 100% as similar to previous cases, the output will be generating automatically. If the case is 1% different from the previous one then the output will be doctor comment. Automatically records all the test reports, patient details, doctor comments, and prescriptions for future treatments.

Model 3 (supporting patient in paying bills) supports the patient is paying a bill using services like insurance companies, drug companies, etc. This could be achieved by implementing Blockchain with AI, all data are recorded includes booking, surgical reports, medicine for treatments, insurance numbers, etc. It also reminds patients how much have to pay for surgery or when the insurance will be claimed.

Yu-Jin Lin, et al., [19] recommended an artificial intelligence integrated with Internet of things(IoT)system for analyzing electrocardiogram (ECG) to detect the cardiac disease. The model of this system made up of two segments. The first segment includes IoT-based wearable ECG sensing device which is patched on the patient front end of the chest, this sensing deviceuploaded the ECG signal at every instant of 24hr to a user interface on smart device's application (APP) through Bluetooth. The second segment consists of a cloud based database used to store each user's ECG signals, which forms a big-data database for AI model, web user interface on APP, AI based algorithms to analyze arrhythmia which is a major cause of heart disorder.

An 8-point moving average filter is used for the primary preprocessing function which removes the noise in the ECGand polynomial fitting is used in the baseline removal to have a suitable input dataset. This paper proposed an AI algorithm based on one dimension Convolutional Neural Networks (CNN) for feature extracting and classifying the arrhythmia.The CNN model consists of four convolutional layers and three fully connected layers. A leaky rectified linear unit is used to prevent several neurons from dead. The three fully connected layers covert 100 number of neurons into 10and again makes these 10 neurons to 4 categories as output. The order of filter order in the convolutional layer is set as 10 and then this order doubles at each following layer. The average accuracyachieved for cardiac disease classification using this algorithm is 94.96%. And also Clinicians can diagnose patients' condition more exactly with the stored ECG data in the cloud server, even patients and their relatives can also get knowledge more about

J.Andrew, et al.,[20] discussed about different types of automatic MRI segmentation techniques in order to identify spinal misalignment which is most concern to find the diseaseslike Stenosis, Scoliosis, Osteoporotic Fractures, Thoracolumbar fractures, Disc degeneration, etc at the earlier stage. Through theirexperimentation study of various Deep learning based segmentation algorithms like Support Vector Machine (SVM) classifier,SegNet, U-Net, Alexnet based Segmentation; they conclude SVM is performing better segmentation in the MRI scan of the spinal to detect the disorders.

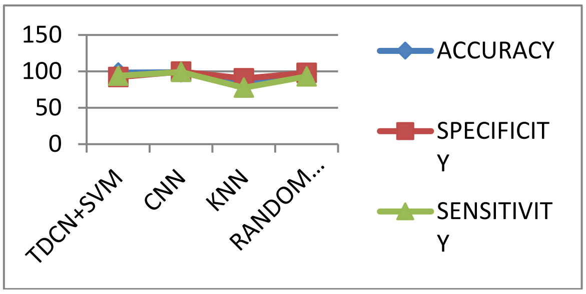

Fig.2. Performance metrics comparision

The classification methods were compared by evaluating various metrics such as Specificity, Sensitivity, IOU (Intersection over Union), Accuracy, Dice Coefficient (DC), Precision among others.

Padideh Danaee, et al., [21] discussed about cancer disease detection using high dimensional and complex gene expression data. The paper presents a deep learning approach for cancer detection, and to the identification of genes dangerous in order to diagnosis of breast cancer. By this model they overcome the limitation of deep learning approaches which required large data sets to predict the disease, mostly not be available for cancer tissues

For analyzing purpose the RNA-seq expre ssion data from The Cancer Genome Atlas (TCGA) database for both tumor and healthy breast samples.These data consist of 1097 breast cancer samples, and 113 healthy samples. An autoencoder (AE) is a feedforward neural network that encodes the high dimensional noisy gene data's into a lower dimensional. The Stacked DenoisingAutoencoder (SDAE) coulddeeply extract functional features from high dimensional gene expression profiles that enable the classification of cancer cells. To classify breast cancer samples from the healthy control samples the new representations method become an effective. Then the lower-dimensional representations were mapping back to the original high dimensional by using the same decoder. Then these data used to analyze and discover highly relevant genes that could play serious roles for cancer prediction and serve as clinical biomarkers for cancer diagnosis.

Ishubham Sharma, et al., [22] discussed about Random forest, K-Nearest-Neighbor (KNN) and Naïve Bayes which all are machine learning algorithms used to predict the breast cancer. By using the Wisconsin Diagnosis data set the performance of the different machine learning algorithm techniques based on the terms accuracy and precision (positive outcomes) has been carried out.

To understand the Machine learning in breast cancer detection, it classified into three segments such as reinforcement learning, supervised learning and unsupervised learning. In supervised learning the output was predicted based on observing the input. The training data is used to generate the functionand controls the system to generate useful epiphanies for new data set introduced to the system. In Unsupervised Learning the machine is mandatory to train from an unlabeled dataset and permitting the algorithm to act on that data without external guidance. In reinforcement learning, the learning process endures from the environment and all possible states are eventually learned by the system over a prolonged period of time. Random Forest is a supervised learning algorithm. The dataset has been divided into training and testing sets, there are 398 observations for training set and 171 observations for testing and the accuracy equals to 94.74%. A k-nearest-neighbor is a supervised learning approach used for regression and classification. To process a new data point, KNN gathers all the data points close by to it. Attributes which have a large degree of variation are key factors in determining the distance.

The accuracy of kNN is found to be 95.90%

N Khuriwal, et al., [23] discussed about the real- world dataset always presented in different format. In order to convert the dataset into an understandable format data preprocessing is a proven method. The data mining technique is applied in preprocessing that used for filter MIAS dataset in a working format. For improve the quality of image they has been used median filter and histogram equalization method. The watershed transform is applied to identify or mark foreground object and background locations. In this work the entropy is standard function for creating texture images. Totally 12 features comprises Mean, Standard Deviation, Kurtosis, skewness, Entropy, Energy , Contrast, Correlation, Homogeneity, Concavity Mean, Symmetry Mean, Class were extracted from the segmented images by using Weiner and Clahe Segmentation. At the final process deep learning is implemented which using Convolutional Neural Networks method. The CNN model is made up of four layers .These collected data features are given to input layer of the convolutional neural networks. The 12 neurons are shrink to 8 neurons for hidden layers and 1 at the output layer. In this paper this CNN model provides a better performance in diagnosis breast cancer with accuracy 98%.

Mamatha Saiyarabarla, et al.,[24] has intended to predict and detect the breast cancer using Random forest algorithm in machine learning.The k-Nearest-Neighbours (KNN) technique is applied for the classification of data in machine learning. The classification can achieved by finding the nearest and similar data points within the equivalent dataset, and a pre-trained guess would depending on that classifications. Euclidean distance is used in performing square the measured dataset which is most acquainted.The method proposed in this model is completed by using python language, the dataset is portioned for training, analyzing and validation. The system will be already trained by giving various datasets initially so that when the user enters the input data it goes through the attributes and its values will be validated and it gives the result. As it has both classification and regression strategies it gives the best accuracy of 73%.

Hafiz TalhaIqbal, et al.,[25] instead of mammography and MRI, thermography (infrared imaging) is an FDA permitted assistant screening tool used in detection of the breast cancer with low cost consumption. This technique comprises of three stages.In the first stage, the infrared camera used to capture thermogram (thermal image), then it is subject to several image processing techniques like histogram calculation for determining Otsu threshold, the breast are located by using Circular Hough Transform (CHT). To segment the thermogram a random Walks algorithm and size reduction is used.At theend of this stage the breast are segmented out from the thermogram.

Next stage is extracting features based on two texture-based matrices, the RLM and GLCM, are computed. The efficient hardware implementation was achieved by carefully selecting the texture features, which are then fed to a dual classifier based on trained Linear Support Vector Machine (LSVM) and convolutional neural network (CNN) to decide the decision boundary. The proposed system achieves an overall sensitivity and specificity of 90.06% and 91.8%

Xinjie Shi, et al., [26] has suggested four deep learning techniques. The two hybrid convolutional recurrent neural network (2D-CNN-RNN and 3D-CNN-RNN) algorithms were designed in detecting Parkinson’s disease based on the task state-EEG signal. In 2D-CNN-RNN the decoded power spectra of EGG as a input to CNN which extracting the spatial information and the RNN structure is for strong modeling power to discover temporal relevance in time-series data by designing a hybrid convolutional recurrent neural network. The CNN structure consists of one layer, in which the kernel performs a spatial filtering over electrodes. The output feature map was then fed to the RNN structure, which includes 350 steps, with each step containing 40 units (i.e., step length). The outputs of the last 50 steps’ states from the RNN structure were fed to fully connected layers, and finally softmax classification layer is obtained. 3D-CNN-RNN: To better process spatial information, a more sophisticated hybrid convolutional recurrent neural network was applied. Compared with 2D-CNN-RNN, the CNN structure was designed with two convolutional layers. In the first layer, the kernel performs a convolution over time, and in the second layer, the convolution operation is performed on the 3D feature map, which could better extract spatial feature compared with 2D-CNN-RNN. All the other structures are exactly the same as in 2D-CNN-RNN

These hybrid algorithms has proven better performance in terms of accuracy 3DCNN-RNN 82.89%, 2D-CNN-RNN 81.13% than two convention deep learning algorithmsconvolutional neural network, CNN 80.89%; and recurrent neural network, RNN 76.00%.

AnujAnand, et al., [27] used different machine learning algorithms as Logistic regression, K-nearest neighbors, Naive Bayes, Support Vector Machine, Decision tree, Random Forest and deep learning algorithms as Deep Neural Networks to efficiently predict the presence of Parkinson's disease. To extract the best features to reduce dimensionality, therefore the maximum variance features of data can be obtained by the two dimensionality reduction techniques- Principal Component Analysis(PCA) and Kernel Principal Component Analysis(KPCA).Then the algorithms are trained with these PCA and KPCA components to provide new set of accuracy and corresponding time complexity.

The logistic regression machine learning algorithm is applied to differentiate whether a person is affected with PD or not. The K-Nearest Neighbor algorithm categorize the object depends on the class most common among its K nearest neighbors.A Support Vector Machine (SVM) is a tool used for the distinct classification of data points by identifying a hyperplane in an N-dimensional space. Random forests feed a new data point in each sub decision tree model which individually makes the prediction.

The results obtained after implementing techniques and compared its performance with their respective accuracies. When PCA was deployed in the algorithms, KNN algorithm provides highest accuracy of 95.52% out of other ML algorithms. When applied with KPCA, saw a severe decrease in the number of features used. Thus, decreasing the time complexities substantially. On the other hand, SVM, Decision tree and Random forest algorithms achieved accuracies as high as 91%, 92% and 93% respectively, while using all the 22 features present in the original dataset.

Shakeel Muhammad Ibrahim, et al.,[28] demonstrates the use of deep learning for the segmentation of heart region from MRI scan. They proposed two types of fully convolutional neural network methods(1) Multi-Channel input scheme (also known as 2.5D method), (2) a single channel input scheme with relatively large size network. These methods are trained using the concept of data driven supervised learning. The heart segmentation from MRI scans can be done by dividing 3D cubes into multiple 2D images. Then trained a convolutional neural network for these 2D image planes, whichengenders desired masks for each input image. To perform segmentation tasks uses the medical segmentation decathlon (MSD) challenge –task 2 dataset which comprises of 20 MRI heart scans. For analyzing purpose they takes three MRI scan images and segmented by using single channel CNN model andconcluded that the segmentation of heart region from MRI scans images with large segmentation region can effectively predicted by implementing a simple encoder-decoder styled CNN model.

Muthu Krishnammal P, et al.,[30] suggested a method is based on the convolutional Neural Networks architecture for brain tumor classification from MRI brain images. These process comprises of three steps, acquiring MRI brain image dataset, and the features are extracted by using two algorithms,discrete wavelet transform (DWT) for extracting wavelet coefficients such as shape, color features and gray-level co-occurrence matrix (GLCM) for statistical features such as texture, energy, contrasts and correlation. The feature are input to the AlexNet, which is a flexible CNN architecture used for categorizing the brain tumor to different classes such as normal, benign and malignant. After classification of tumor images, segmentation of tumor part is through K-mean segmentation algorithm which segregates the tumor part in the rest of the image. At last they conclude the method of deep learning provides better accuracy in classification and segmentation stages.

Baidaa Al-Bander,et al., [31] discussed about a deep learning method for detecting glaucoma in colored retinal fundus images by developing an automatic feature learning technique.A pretrainedconvolutional neural network (CNN) model Alexnet which consists of 23 layers to extracts the features from the retinal input image todiscriminate between normal and glaucomatous patterns for diagnostic decisions. Then the extracted features are fed intoSupport Vector Machine(SVM) classifier for training. After evaluated the test image the SVM classifier categorizing the test data into either normal or glaucoma infected one. Instead of CPU, GPU is used to increase the computational speed as CNN's are highly computationally intensive. The data used in this learning is uptoto 455 high-resolution glaucoma and non-glaucoma images. They experimenting this model and achieved an accuracy, specificity and sensitivity of 88.2%, 90.8%, and 85%, respectively which compared favorably to the-state-of-the-art but at considerably lower computational cost.

AvulaBenzamin, et al., [32] proposed a method to detect the Diabetic Retinopathy by using Deep learning algorithm. By detecting the hard exudates in the retinal fundus images, the DR could be easily predicted because the hard exudates exist when the Diabetic retinopathy is present. The dataset to work on the retinal image was downloaded from IDRiD. In the dataset the pixels of ground truth images having 1 intensity for all exudates pixels and 0 for all remaining pixels. The dataset of fundus image consists of 54 images which is divided into two sets such as training set and testing set. The network is trained on 20,000 image patches on size 32*32, then confusion matrix is used to predict the pixels in the images are belong to hard exudates and background patches based on the intensity. This model has anticipated all the test image patches with an accuracy of 98.6%, sensitivity of 98.29% and Specificity of 41.35%.

Hui-Ting Hong, et al,. [34] has proposed a paper to recognize the pain of the patient through the facial expression and audio expression features. There is difference between pain and no pain face expressions with the patients, so the author has created a framework (TSEN-SLO) that combines the relationship between the pain level and pain site to be automatically detected. This relationship is captured using the learnable tensor, every other information is also a part of the encoding branch. This framework achieves 70% pain level classification (severe vs. mild), 48.1% when pain level is classified as mild, moderate, severe. The audio video pain triage database is actually obtained from the hospitals and the system is trained based on that in three levels like i) acoustic features, ii) Facial features, iii)Session-level behavior encoding. Further analysis is done to find the differences between the severe and mild pain specifically when the patient is having stomach pain and headache and the statistical deviation are derived. Then a two sided test is performed among the pain level and pain site with a significant level of 0.05 as cut-off value.

Conclusion

We have reviewed many papers which discusses about how AI can be used in healthcare in different ways detecting, diagnosing, treating and also following the post surgery patients. We have also discussed about the maintaining the health records of the patients electronically in such a way it can be retrieved at any time using 5G communication & IoT and can also be used to update the learning process of AI used in smart devices [8,11,12]. We have also reviewed about the successful AI systems using ML, deep learning and NLP for accurately diagnosing or detecting the cancer in different parts from the images [23,24,25]. A bayesian network is used in the prediction of the osteomylitis in children [13], a deep learning technique was used in the spine image segmentation [20] which helps the clinicians to treat the patients at the earliest. We also reviewed how the images of ECG for cardio [14], EEG for brain and neuro [2,15,17,26,27] predicting parkinson's disease and melanoma were precisely analysed and detected by AI. It has shown its excellence in predicting the glaucoma and retinal diseases using deep learning techniques[31,32]. We never failed to review about the smart wearable devices having the sensors which helps in monitoring the patients in absence of the attender or patients in the post operated period.[12, 19]. Also about the smart medicine recognition system for visually impaired [16]. As an improvement in the technique, a pain level recognition system is developed using AI which will be very useful for the doctors to identify the intense of the pain of the patients. Our future work will be focused in developing a smart device or a system which is even more precise in sorting out the diseases.

References

Jennifer Bresnick., Feb-28-2019.https://healthitanalytics.com/news/healthcare-ai-to play-major-role in-15.7-trillion-economic-boost.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H. and Wang, Y., 2017. Artificial intelligence in healthcare: past, present and future. Stroke and vascular neurology, 2(4), pp.230-243.

ARDS Definition Task Force*., Singer, M., Deutschman, C.S., Seymour, C.W., Wildman, M., Sanderson, C., Groves, J., Wildman, M.J., Sanderson, C., Groves, J. and Mnih, V., 2019. Artificial intelligence in healthcare: past, present and future. Journal of the Intensive Care Society, 20(3), pp.268-273.

Bishnoi, L. and Singh, S.N., 2018, January. Artificial intelligence techniques used in medical sciences: a review. In 2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 1-8). IEEE.

Shailaja, K., Seetharamulu, B. and Jabbar, M.A., 2018, March. Machine Learning in Healthcare: A Review. In 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 910-914). IEEE.

Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., Van Der Laak, J.A., Van Ginneken, B. and Sánchez, C.I., 2017. A survey on deep learning in medical image analysis. Medical image analysis, 42, pp.60-88.

Lee, J.G., Jun, S., Cho, Y.W., Lee, H., Kim, G.B., Seo, J.B. and Kim, N., 2017. Deep learning in medical imaging: general overview. Korean journal of radiology, 18(4), pp.570-584.

Najafabadipour, M., Zanin, M., Rodríguez-González, A., Torrente, M., García, B.N., Bermudez, J.L.C., Provencio, M. and Menasalvas, E., 2020. Reconstructing the Patient's Natural History from Electronic Health Records. Artificial Intelligence in Medicine, p.101860.

Macías-García, L., Martínez-Ballesteros, M., Luna-Romera, J.M., García-Heredia, J.M., García-Gutiérrez, J. and Riquelme-Santos, J.C., 2020. Autoencoded DNA Methylation Data to Predict Breast Cancer Recurrence: Machine Learning Models and Gene-Weight Significance. Artificial Intelligence in Medicine, p.101976

Lauritsen, S.M., Kalør, M.E., Kongsgaard, E.L., Lauritsen, K.M., Jørgensen, M.J., Lange, J. and Thiesson, B., 2020. Early detection of sepsis utilizing deep learning on electronic health record event sequences. Artificial Intelligence in Medicine, p.101820.

Ahamed, F. and Farid, F., 2018, December. Applying Internet of Things and machine-learning for personalized healthcare: issues and challenges. In 2018 International Conference on Machine Learning and Data Engineering (iCMLDE) (pp. 19-21). IEEE.

Mohanta, B., Das, P. and Patnaik, S., 2019, May. Healthcare 5.0: A paradigm shift in digital healthcare system using Artificial Intelligence, IOT and 5G Communication. In 2019 International Conference on Applied Machine Learning (ICAML) (pp. 191-196). IEEE.

Wu, Y., McLeod, C., Blyth, C., Bowen, A., Martin, A., Nicholson, A., Mascaro, S. and Snelling, T., 2020. Predicting the causative pathogen among children with osteomyelitis using Bayesian networks–improving antibiotic selection in clinical practice. Artificial Intelligence in Medicine, p.101895.

Sangaiah, A.K., Arumugam, M. and Bian, G.B., 2020. An intelligent learning approach for improving ECG signal classification and arrhythmia analysis. Artificial Intelligence in Medicine, 103, p.101788.

Calhas, D., Romero, E. and Henriques, R., 2020. On the use of Pairwise Distance Learning for Brain Signal Classification with Limited Observations. Artificial Intelligence in Medicine, p.101852.

Chang, W.J., Yu, Y.X., Chen, J.H., Zhang, Z.Y., Ko, S.J., Yang, T.H., Hsu, C.H., Chen, L.B. and Chen, M.C., 2019, March. A deep learning based wearable medicines recognition system for visually impaired people. In 2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS) (pp. 207-208). IEEE.

Kaplan, A., Güldogan, E. and Arslan, A.K., 2019, September. Prediction of Melanoma from Dermoscopic Images Using Deep Learning-Based Artificial IntelligenceTechniques. In 2019 International Artificial Intelligence and Data Processing Symposium (IDAP) (pp. 1-5). IEEE.

Le Nguyen, T. and Do, T.T.H., 2019, August. Artificial Intelligence in Healthcare: A New Technology Benefit for Both Patients and Doctors. In 2019 Portland International Conference on Management of Engineering and Technology (PICMET) (pp. 1-15). IEEE.

Lin, Y.J., Chuang, C.W., Yen, C.Y., Huang, S.H., Huang, P.W., Chen, J.Y. and Lee, S.Y., 2019, March. Artificial Intelligence of Things Wearable System for Cardiac Disease Detection. In 2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS) (pp. 67-70). IEEE.

20. Andrew, J., DivyaVarshini, M., Barjo, P. and Tigga, I., 2020,March. Spine Magnetic Resonance Image Segmentation Using Deep Learning Techniques. In 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 945-950). IEEE.

21.Danaee, P., Ghaeini, R. and Hendrix, D.A., 2017. A deep learning approach for cancer detection and relevant gene identification. In PACIFIC SYMPOSIUM ON BIOCOMPUTING 2017 (pp. 219-229).

22. Sharma, S., Aggarwal, A. and Choudhury, T., 2018, December. Breast Cancer Detection Using Machine Learning Algorithms. In 2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS) (pp. 114-118). IEEE.

23. Khuriwal, N. and Mishra, N., 2018, November. Breast Cancer Detection From Histopathological Images Using Deep Learning. In 2018 3rd International Conference and Workshops on Recent Advances and Innovations in Engineering (ICRAIE) (pp. 1-4). IEEE.

24. Yarabarla, M.S., Ravi, L.K. and Sivasangari, A., 2019, April. Breast Cancer Prediction via Machine Learning. In 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 121-124). IEEE.

25. Iqbal, H.T., Majeed, B., Khan, U. and Altaf, M.A.B., 2019, October. An Infrared High classification Accuracy Hand-held Machine Learning based Breast-Cancer Detection System.

In 2019 IEEE Biomedical Circuits and Systems Conference (BioCAS) (pp. 1-4). IEEE.

26. Shi, X., Wang, T., Wang, L., Liu, H. and Yan, N., 2019, November. Hybrid Convolutional Recurrent Neural Networks Outperform CNN and RNN in Task-state EEG Detection for parkinson's Disease. In 2019 Asia-Pacific Signal and information Processing Association Annual Summit and Conference (APSIPA ASC) (pp. 939-944). IEEE.

27. Anand, A., Haque, M.A., Alex, J.S.R. and Venkatesan, N., 2018, December. Evaluation of Machine learning and Deep learning algorithms combined with dimentionality reduction techniques for classification of Parkinson’s Disease. In 2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) (pp. 342-347). IEEE.

28. Ibrahim, S.M., Ibrahim, M.S., Usman, M., Naseem, I. and Moinuddin, M., 2019, December. A Study on Heart Segmentation Using Deep Learning Algorithm for MRI Scans. In 2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS) (pp. 1-5). IEEE.

29. Stephen Sagayaraj.A., Mohanapriya.G., Nivetha.R., Subhashini.C., Suganya.V., 2017, Segmentation of breast cancer using texture method in Mammogram image.In 2017International journal of modern trends in Engineering and science.

30. Raja, S.S., 2019, May. Deep Learning Based Image Classification and Abnormalities Analysis of MRI Brain Images. In 2019 TEQIP III Sponsored International Conference on Microwave Integrated Circuits, Photonics and Wireless Networks (IMICPW) (pp. 427-431). IEEE.

31. Al-Bander, B., Al-Nuaimy, W., Al-Taee, M.A. and Zheng, Y., 2017, March. Automated glaucoma diagnosis using deep learning approach. In 2017 14th International Multi-Conference on Systems, Signals & Devices (SSD) (pp. 207-210). IEEE.

32. Benzamin, A. and Chakraborty, C., 2018, June. Detection of hard exudates in retinal fundus images using deep learning. In 2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR) (pp. 465-469). IEEE.

33. Kabilesh, S.K., Revathi, K., Sabitha, K. andSujithkumar, N., 2020. Medical Image Counterfeit Detection for. SmartHealthcare. Journal of Sensor Research and Technologies, 2(2).

34. Hong, H.T., Li, J.L., Chang, C.M. and Lee, C.C., 2019, September. Improving Automatic Pain Level Recognition using Pain Site as an Auxiliary Task. In 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 284-289). IEEE.