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An Empirical Survey on Early Health Condition Prediction based on Clinical Parameters

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***Abstract*—Healthcare experts need accurate estimates of the outcomes of various diseases that patients suffer from. In addition, time is another important feature that affects clinical choices for accurate predictions. When there is a sickness in the body, the human body offers symptoms in the form of discomfort, changes in bodily parameters, changes in habits, and a variety of other changes. These changes are frequently assessed in order to detect a specific type of sickness. For example, Fluctuations in the blood glucose level is used to identify diabetes, whereas variations in the electrocardiogram signals are used to detect heart disease and other cardiac diseases. Although these diseases are frequently linked to one another, developing a crossover parametric model for each of them can help to improve the precision with which they are recognized. For example, analyzing the influence of fluctuations in blood sugar levels can be connected to the identification of cancer because long-term glucose consumption weakens the body and consequently diminishes its immune system's effectiveness. This decline in immunity causes a reduction in red blood cells, making the body more susceptible to malignancy. Many cases of cross parameter illness detection have been investigated over the years, and the results have been promising. Here several systems are compared which perform cross-analysis of cancer, cardiovascular disease, and diabetes. It first tests different cross-body parameter links between these diseases, and then tests the classification efficiency of a several machine learning / deep learning algorithms for detection of diseases by using cross-body parameters tested earlier. When compared to non-cross parametric techniques, it has been discovered that the system increases the accuracy of detection of various disease. In this paper we have examined few papers according to their methods, styles, actions, and procedures.**

***Index Terms*— body parameters, disease, immunity, cross-parameter, neural, network, disease prediction, machine learning.**

I. INTRODUCTION

The person's body is amongst the most effective interdependent systems of organs ever devised, and it is also one of the most complex. The functioning of each part of the body is intertwined with the other organs. The heart, in addition to being the source of energy for the other organs, is reliant but at the other organ systems because of its long-term functioning. Ref. [1] Taking the example of meaty meals, the vessels of the heart might get blocked as a result of cholesterol deposition; on the other hand, by ingesting liquids and green vegetables, the heart's functioning improves. As a result of this improvement, the functioning of other body organs is improved as well. For example, maintain a positive heartbeat results in improved kidney and liver functions. It also has the

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added benefit of improving cognitive functions and the digestive system. Ref. [2] If an individual with something like a healthy immune system has poor eating habits, gases are produced in the body as a result of inefficient digestion. This type of gas has an adverse effect on the chest and abdomen, preventing adequate blood and oxygen delivery to the body. This has an effect on the heart's ability to function. Ref. [3] As a result, all of the body's functions are interconnected, and for the human body to function efficiently, all of its organs must perform efficiently.

Following Fig.1 shows the categorization of clinical parameters from which we can take human health records reading in the form of text, image or signals. Clinical parameters are mainly categorizing into 4 types as general parameters (weight, height, age, gender, etc.), Laboratory parameters (BP, Glucose, Cholesterol, etc.) which we get by using several pathology test or blood and urine, Medical imaging parameters such as CT scan, radiographs(X-Ray), MRI and Signal based parameters (ECG, EEG, etc.) from which we can get heart beats reading or working of human brain activity. These all parameters play significant role in the detection of diseases and monitoring human health condition.

The general disease prediction method forecasts the likelihood of a disease based on a patient's symptoms. Guidance on treatment will be provided. The system will take data from various sources mainly subjects, then the data will be preprocessed (understanding, cleaning, noise reduction, feature selection) and further given to the final system.

The system will be taught to forecast illness based on the user's input data using data mining methods. Data Preparation, Understanding and Cleaning the Data, Extracting Features, and Regression or Classification algorithms are the major steps in the system performance.

The important steps that are carried out throughout the disease prediction system are simplified and shown in the below Fig 2.

II. Literature Review

A. Clinical Parameters

Section A recommended multi parametric categorization model which uses clinical parameters for the disease prediction is discussed below. First, the theory that underlies the selection of different classification parameters are demonstrated, then the actual classification algorithm based on machine learning model and deep neural networks is demonstrated. The provided model is capable of accurately classifying heart disease, cancer, and diabetes with a high degree of effectiveness. Furthermore, the studied systems are adaptable, it will be easier to incorporate different features and disease kinds in the construction of an aggregative categorization system in the future.

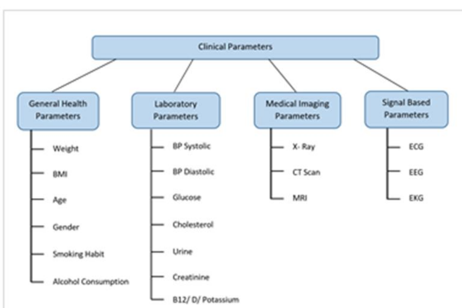

Fig. 1. Broad categorisation of clinical parameters

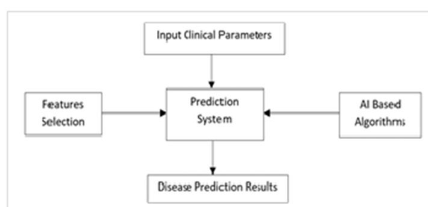

Fig. 2. Block diagram of disease prediction system

Selection of different clinical parameters:

The below mentioned clinical parameters were agreed upon for each of the diseases while going through the various features for the prediction of that disease. Heart disease, cancer, and diabetes like diseases are considered for text / numeric data. Following are several general clinical parameters that are used for the detection of disease;

- Heart disease prediction features: Age, education, gender, does the person smoke, cigarettes per day, medication of blood pressure, any prevalent stroke, prevalent hyper-tension, diabetes, total cholesterol level, systolic BP, diastolic BP, body mass index, glucose levels, heart rate, etc.

- Cancer prediction features: Age, Gender, Air Pollution, Alcohol use, Dust Allergy, Occupational Hazards, Genetic Risk, chronic Lung Disease, Balanced Diet, Obesity, Smoking, Passive Smoker, Chest Pain and Coughing of Blood, etc.
- Diabetes prediction features: Glucose Before fasting, Glucose Anytime, Age, Gender, Blood Pressure, Family member with Diabetes past or present, BMI, Pregnancies, percentage of occurring diabetes, Polyuria, Polydipsia, sudden weight loss, weakness, Polyphagia, Genital thrush, visual blurring, Itching, Irritability, delayed healing, Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, Diabetes Pedigree Function, etc.

While performing providing a good between the characteristics of various diseases including their respective dependencies, the following Table I was discovered.

TABLE I. CROSS DEPENDENCY OF FEATURES ON DIFFERENT DISEASES

Relation	Feature 1	Feature 2	Feature 3
Heart Diseases to Diabetes	BMI 60%	Diabetes 45%	Glucose 40%
Diabetes to Cancer	Weight Loss 20%	Obesity 15%	Genetic History 55%
Cancer to Heart Diseases	Smoking 75%		

Table II shows the heart disease, cancer and diabetes disease prediction accuracy of various algorithms and Fig. 3 shows the graphical representation of the accuracy comparison of various disease.

TABLE II. ACCURACY COMPARISON OF DISEASES

REF	Algorithms	Disease	Accuracy
[7]	SVM	Heart	87
[8]	Deep CNN	Heart	91
[10]	Fuzzy Logic	Diabetes	97
[12]	CNN	Cancer	87
[17]	T2D	Diabetes	90

B. ECG

ECG provides information on the heart's morphology and function, which are utilized to anticipate different cardiac diseases. The raw ECG signal has important properties for detecting heart arrhythmia. The analysis uses ECG characteristics such heart rate, QRS complex, PR interval, ST segment elevation, and ST interval. These ECG characteristics diagnose atrial fibrillation, sinus tachycardia, myocardial infarction, and apnea.

Various approaches are used to identify ECG characteristics. Ref. [22] The authors have employed multi-scale discrete wavelet transform peak detection to locate the peak and extract foetal characteristics from ECG. The fluctuation in foetal heart rate has been used to create diagnostic indices for prenatal growth monitoring. Ref. [23] used EMD to diagnose cardiovascular disorders. Using time domain analysis, RR intervals, SDNN of RR intervals, variance and differences of root mean square (rms) values of consecutive RR intervals were computed. Ref. [21] Cardiovascular problems and ischemia were discovered using ECG signals. Ref. [24] uses a neural fuzzy technique to identify myocardial infarction arrhythmias using back propagation neuro networks (BPNN). Ref. [25] The authors have suggested a LABVIEW virtual instrumentation system for heart disease diagnosis that automatically removes noise and filters the raw ECG data. Ref. [26] suggested an ANN-based cardiac arrhythmia detection method that separates illness into normal and pathological categories. Table III provides numerous ECG signal characteristics indicating various heart diseases and Table IV provides accuracy comparison of various researchers to predict the disease.

TABLE III. VARIATION IN DIFFERENT FEATURES OF ECG SIGNAL SHOWING DIFFERENT CARDIAC DISORDER

Heart Beat (BPM)	PR Interval	QRS Complex	P Wave (mV)	Heart Condition
60-100	0.12-0.2	0.04-0.12	<0.25	Normal Sinus Rhythm
400-600	Not Visible	-	absent	Atrial Fibrillation
>100	0.12-0.2	0.04-0.12	<0.25	Sinus Tachycardia
60-67	0.12-0.2	0.04-0.12	-	Apnea

C. MRI

Medical imaging data is one of the greatest and most sophisticated sources of patient information. Alzheimer's disease causes memory loss and lowers quality of life. Alzheimer's Disease (AD) is the most prevalent type of dementia that causes gradual memory loss and impairment of everyday activities. The system utilises brain MRI images to diagnose Alzheimer's disease. Currently, physicians and radiologists use MRI to diagnose illness. Table V compares ML/DL algorithms that utilise MRI images to predict Alzheimer disease.

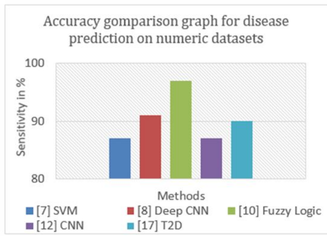

Fig. 3. Accuracy Comparison of disease Prediction on numeric dataset

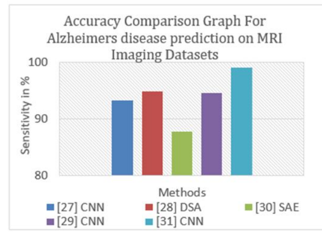

Fig 4. Accuracy comparison Graph

TABLE IV. ACCURACY COMPARISON OF ALGORITHMS FOR PREDICTING VARIOUS DISEASE ON ECG DATASET

REF	Disease	Algorithms	Accuracy
[21]	Ischemia	ST-Segment, T-Wave	94.42
[22]	Fatal Growth Monitoring	Multi Scale Discrete Wavelet Transform	99.50
[23]	Cardiovascular Diseases	EMD , Time Domain Features, SDNN	97.74
[24]	Myocardial Infarction	NEURAL FUZZY BPNN	99.10
[25]	Heart Disease Detection	LABVIEW	91.12
[26]	Cardiac Arrhythmia	ANN	86.67

TABLE V. COMPARISON OF ML/DL ALGORITHMS TO PREDICT ALZHEIMER DISEASE

REF	Algorithm	Accuracy
[27]	CNN	93.18
[28]	DSA	94.80
[30]	Stacked Auto encoders	87.76
[29]	CNN	94.54
[31]	CNN	99.00

D. CT Images

Due to the absence of overlapping tissues and the simplicity of examining illness and its location, CT scans give a window into pathophysiology that might shed light on numerous phases of disease detection and evolution. A rapid COVID-19 diagnosis using 3-D chest CT images may save lives. Ref. [32] Authors have employed a CNN + RNN network to distinguish between COVID19 and non-COVID-19 situations. Using volumetric 3-D CT images, [33] used 3-D ResNet models to identify COVID-19 and differentiate it from other common pneumonia (CP) and normal patients. Ref. [34] proposed employing 3-D CT volumes for COVID-19 classification and lesion localization. A pre-trained UNet segmented the lung area of each CT scan slice, which was then passed into a 3-D DNN for classification. Ref. [35] employed an inflated 3D ResNet50 model with non-local operations on the second and third layers. They employed label smoothing to alleviate over-fitting. To accommodate the varying length of CT-Scans, they employed sub-sampling or padding for lengths over or below 128. The final forecast is based on a majority vote system of the remaining findings. [36] enhanced a vision transformer to learn 3D CT-scan features to diagnose COVID-19. Their network has two major stages. Then the classification model was implemented, with features extracted from each slice using Swin transformer, then aggregated into a 3D volume level feature using a max pooling layer.

Ref. [37] A 3D CNN with BERT was utilized to categories the CT-scan volumes. They used morphological transformation and a pre-trained UNET network to segment the original CT data. Then they re-sampled a collection of slice pictures for training and validation. This pick required a threshold for the proportion of lung masks in the picture. The fixed size volume was then input into a 3D CNN with BERT classification model. Each CT-scan was given an embedding feature vector, which was then transmitted to an auxiliary classification layer using an MLP classifier. Ref. [36] employed an AutoML automated process to save time and money. They employed 2D CNN pre-trained models like VGG, ResNet, and DenseNet. Instead of 3D volume, 2D CNNs were trained. Slice-by-slice evaluation First, 2D slices were predicted, and then the most common predictions were allocated as 3D picture labels. F1 score comparison of various algorithms to detect COVID19 using CT Images is shown in Table VI.

TABLE VI. F1 SCORE COMPARISON

REF	Algorithms	F1 Score
[35]	ResNet50	90.06
[37]	CNN with BERT	88.22
[36]	VGG	87.77

E. EEG

EPILEPSY is a set of neurological illnesses defined by a lasting propensity to induce recurrent seizures. Epilepsy is caused by the normal brain network firing neurons in a self-sustaining hyper-synchronized way in the cerebral cortex.

TABLE VII. SUMMARY OF ML METHODS USED FOR ES PREDICTION

REF	Features	Algorithm	Sensitivity
[38]	HP, SpM, Entropy, ApEn	SVM	92.23%
[39]	HP, Standard Deviation, Skewness, Entropy	KNN	97.44%
[40]	DWT Coefficient	SOM	98%
[41]	Fuzzy Rules	SVM	96.6%

Acute neurological insults (such as stroke, brain trauma, metabolic disturbances, and drug toxicity) may cause convulsions and seizures without necessarily indicating a long-term predisposition to recurrent unprovoked seizures (i.e. epilepsy). An epileptic seizure (ES) is a brief aberrant electrical discharge that occurs in the cerebral networks. To avoid the attack using drugs, it is useful if we could predict the attack. Pre-processing and feature extraction from EEG signal, is always useful to improve on prediction time and maximizing the true positive rate (TPR). Signal-to-noise ratio (SNR) is improved by performing pre-processing to remove noise from the signals.

III. RESULT AND DISCUSSION

In order to evaluate the classification methods and infrastructures available in the literature over the past couple of years, it is necessary to provide a bird's eye view that can categories these algorithms according to the illnesses generally categorized, the characteristics used for classification, and the underlying accuracy achieved. These methods will assist the readers in evaluating different algorithms and determining which ones should be used for either cross-parametric multi-disease detection or single-source parameter with multi-disease detection.

The application of these interconnected factors for the detection of various types of diseases is discussed in the following section. Afterwards, the accuracy and other classification metrics obtained by using the discussed approach are compared to those obtained by using existing non-cross-linkage algorithms in the following section. Every one of those datasets contains a high quantity of information for the specific illness type being studied, all of the selected parameters are fed into the system and indeed the results indicated in Table VIII are the findings that were produced. Every one of these networks was trained on number of the datasets, and the accuracy with which they detected the diseases are shown.

IV. CONCLUSION

In research work we have used number of input parameters which includes clinical, laboratory, imaging such as MRI / X-ray, CT- Scan, EEG, ECG, etc. to predict the diseases such as heart, diabetes, cancer, COVID19, epileptic seizure, Alzheimer's disease, etc. From survey it can be seen from the findings that the DL based algorithm is extremely good at detecting various types of diseases based on these various features. This seems to be attributable to the fact that the several listed technique conducts preliminary pre-calculation of the feature extraction and feature importance calculation before going on to do actual network training in the following step. Whenever tried to compare to all of the other component feature sets, the total number of features available for categorization is increased as a result of this pre-calculation. This enhanced selection of features improves the accuracy of the network's disease detection and, as a result, decreases the quantity of inaccuracies throughout classification. Furthermore, the network's output provides a likelihood of disease occurrence in the input data based on the network's input data. This likelihood can be used to analyze the patient's health issues over a longer period of time. However, the accuracy of individual illness diagnosis is low, and it may be improved by replacing the present computational model with a deep CNN, or by adding additional in-depth hypothesis for the interrelated features, in addition to substituting neural network. Furthermore, a plethora of other diseases and their interconnected characteristics can be integrated into the system in order to evaluate its long-term performance on big datasets and to test the system in real-time scenarios.

TABLE VIII. SUMMARY OF ML METHODS USED FOR ES PREDICTION

REF	Method	Training Acc. (%)	Testing Acc. (%)	Validation Acc. (%)
[8]	Deep CNN	95%	91%	86%
[9]	DNN	91%	86%	85%
[10]	Fuzzy logic classifier	97%	95%	92%
[11]	ANN	95%	91%	84%
[12]	CNN	87%	86%	85%
[13]	SVM	93%	91%	85%
[14]	LogitBoost	96%	93%	90%
[15]	MetaNN	97%	91%	84%
[19]	CNN	96%	91%	86%
[20]	LBP, PCA with NN	96%	91%	83%

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