

# A Computational Intelligence Paradigm with Human Computer Interface Learning

Kiran J Waghmare, Reeya S R

**Abstract:** *The cognitive Science is the leading technology which works on the principle of Neuroscience. Human Computer Interface is a challenging approach in neurosciences, which is the leading method to handle the brain activities to control external communications with the electronic devices for physically challenged human beings. The various HCI applications are developed with this advance technology. This helps in various patients which are physically challenged or facing the lock in syndrome, a condition where limbs are not functioning to full extent. Therefore, this paper is the review paper to the various EEG signal classification techniques using different taxonomy with techniques like linear, nonlinear, stable-ubstable, static-discriminant to design various HCI applications.*

**Keywords :** *Human Computer Interface; learning; brain activity; signal pattern; classification;*

## I. INTRODUCTION

The rapid growth in Cognitive Science is the interdisciplinary study of mind and intelligence termed as Neuroscience. Technically, the study of neuroscience combined with Computer Engineering created innovative neurotechnology called as Human Computer Interface (HCI). HCI is a revolutionary technology involving communication system to external environment using brain control activity[8]. This paper discusses the HCI systems with rhythmic pattern recognition and their challenges with learning models.

### A. Human Computer Interface

Human-Computer Interface (HCI) is a bidirectional communication route between brain activities and devices connected externally without outlaying any neurological dependency [5]. Therefore it is also termed as Man Machine Interface. In today's date, Human-Computer Interface has many applications reached beyond medical applications like, Neuro based Smart environment, Neuromarketing and advertising, self-regulation, games and entertainment etc. It is used to enhance, improve, the skill of different people working in different areas, or it can be used as a research tool.[3]. Therefore in order to control various HCI applications with control over external devices,

different signal patterns can be generated to translate the commands over external devices. It means that the HCI science achieving the heights not only as a communication tool for many physically challenged people to perform their day to day activities, but also capturing more attention towards rehabilitation of people. Even though, the number of HCI challenges are to be solved by research experts or scientist.[6] However, some of the real world challenges in HCI are listed below:

- *Reduced signal strength in HCI:* The Human signal patterns are highly variable. Therefore, the high erroneous rate is expected at acquired signal.
- *Reduced bandwidth during data transfer:* The get the accurate control over application, high data transfer rate is required for fast response
- *Error rate inclined to increase:* Due to condensed signal communication frequency and the reduced bandwidth with weaker data transfer rate strength, error probability always increases.
- *Classification of Signal inaccurately:* The accurate signal classification depends upon signal acquisition method captured from the electrodes. The accuracy of classification completely varies from various learning models algorithms.

In order to understand the HCI Human signal patterns communications through the Human activities, the electrodes can be placed in different methods i.e., Invasive BCI, Partially Invasive BCI and Non-Invasive BCI[1] as depicted in the following figure 1[5][12]

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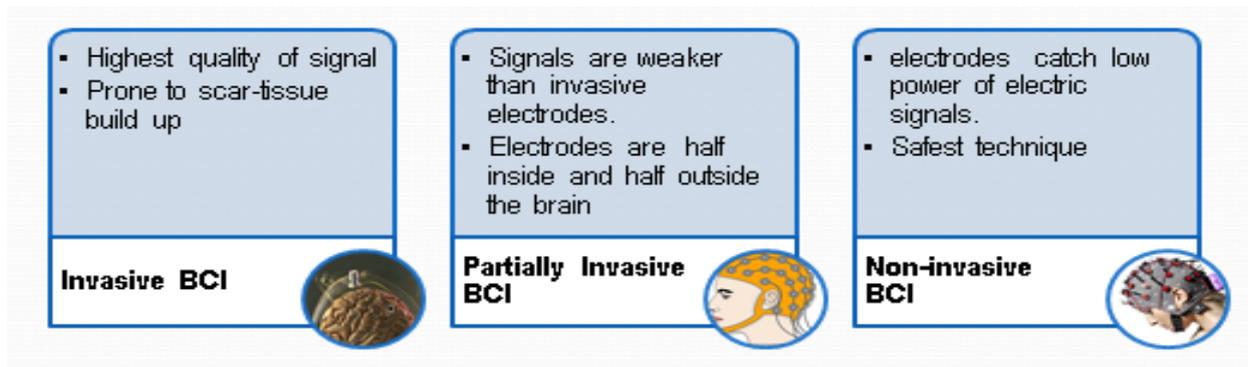
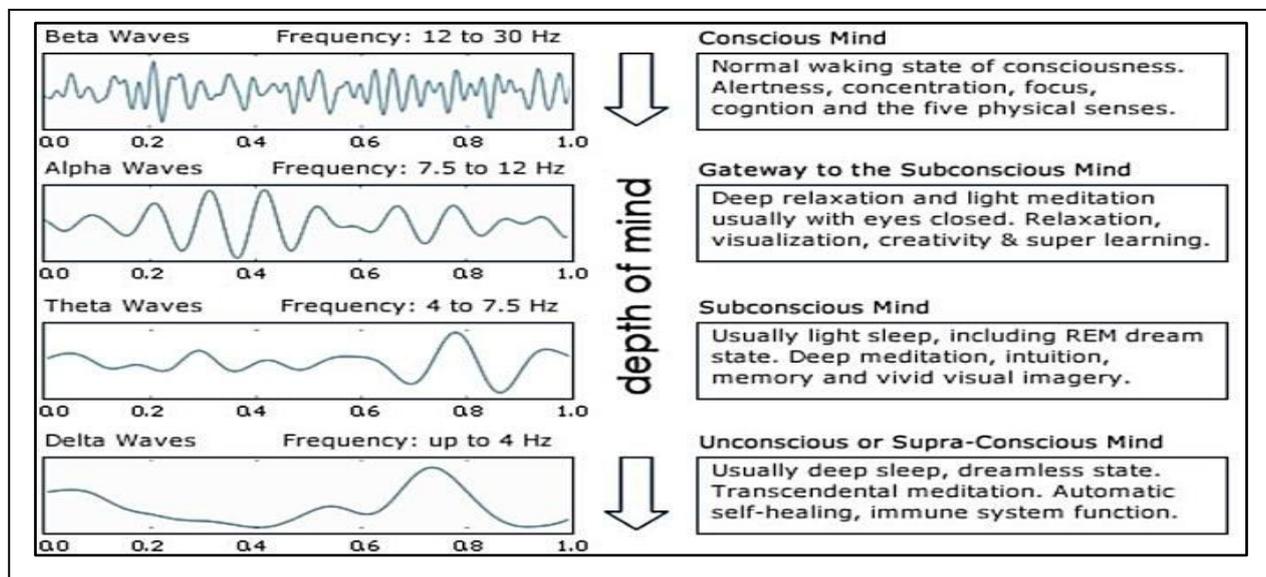


Fig. 1.Types of HCI for Signal Acquisition

**B. Rhythmic Patterns Recognition of Acquired Signal**

The neuron activities in Human are the responsible factor for communication through thoughts, emotions and behavior. They produced electronic pulses from neurons mass communication with each other. These electrical activity are detected with the help of electrodes placed in Invasive , partially invasive and non-invasive type of HCI.

These electrical activity is display as different signal patterns from higher to lower frequency range as shown in given figure2.These signal patterns are measured in electronic Human wave signal patterns [2][3]called as Electroencephalography (EEG) [10]. EEG can be interpreted by various Human wave signals i.e., Delta waves , Theta waves, Beta Waves and Alpha waves.[11][7]



**II. HUMAN COMPUTER INTERFACE MATHEMATICAL MODEL**

The Basic working model for HCI applications generally consist of 3 module i.e., Signal Acquisition (Input to HCI System), Signal Processing and Resultant Classifiers commands for HCI application(Output to HCI system )

- Module 1: Signal Acquisition:** Basically it is a input to the system, which may be in the form of Invasive, Partially invasive or non-Invasive Human activity signal captured from the scalp from several neurons activity. This is a low frequency band signal, hence required to be amplified. Then it can be used as input in digitized form[10].

- Module 2: Signal Processing:** The input signal obtained from module 1 contains noise, therefore to analyse

the signal various operations are required like., Pre-processing, Feature Extraction and Classification.

- a) **Pre-processing:** The obtained signal is a raw EEG signal required to apply filters, Due to this clear detection of feature is possible .

- b) **Feature Extraction:** By applying filters different features can be detected, it is easy to identify the required specific features for analyse and remove the unwanted signal specification, which may direct to wrong results.

- c) **Classification:** Once the required feature are obtained , then apply the classification and translation algorithms based on HCI application. The EEG signal patterns can be classified based on various classifiers like frequency, shape, time period etc[34][28].

- Module 3: Resultant Classifier:** As a result of classification the HCI applications output can be manipulated from the classifier result.

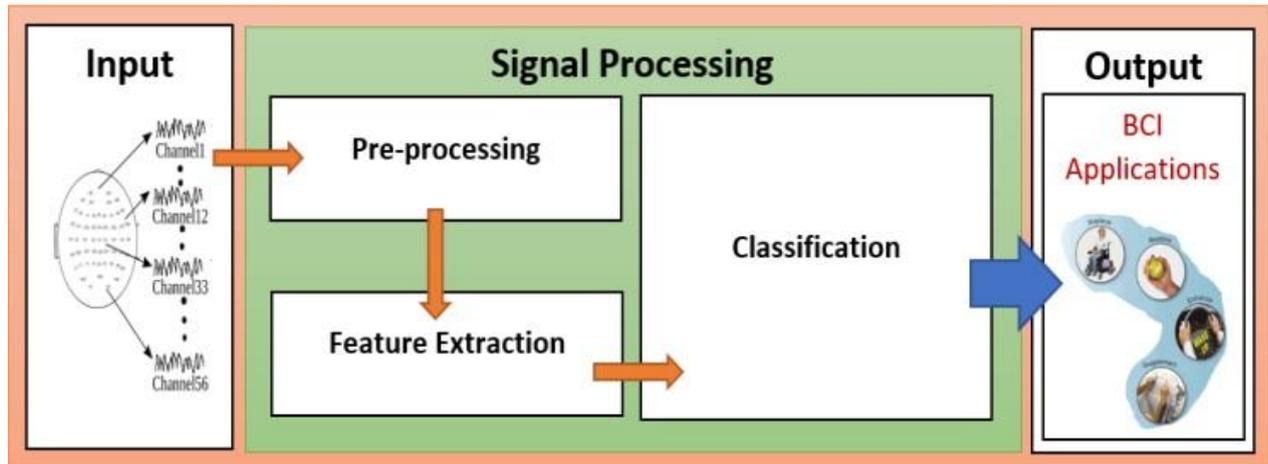


Fig. 3. Mathematical Model for Human Computer Interface

### III. MATERIAL AND METHODOLOGY

HCI application decides the input signal patterns and the classification algorithm to be used for various applications.[15].To run the HCI application proper training of classifier to recognize most relevant features which leads to best classifier result is must. Otherwise it may lead to time variation of EEG signal patterns and may arise various HCI challenges in Classification as follows:[33][34].

A. *The Curse of dimensionality*: The phenomena that arise while handling the data in high dimensional spaces that do not occur in low dimensional setting .[26] The number of records that needed to describe requires dimensionality to be increase exponentially [9]. The common challenge in HCI application is to increase the dimensionality with small datasets.

B. *Time Variance in EEG signal*: As the bandwidth of

Human signal patterns varies from time to time, which results into various Humanwave signal pattern generation. These signal varies from peson to peson , time to time, task to task and application to application. otte et al. (2007) lists a range of approaches that have been used differently to handle the issues like combining time segments differently and for different combinations too[27].

C. *Bias-Variance Dilemma*: Noise is an irreducible error in HCI System, Bias represents deviation between the actual and estimated mapping, which relies on the selection of classification algorithm and variance imitates the sensitivity of the training set.[9] Therefore to reduce the error involved in classification, bias and variance must be less[26].

D. *Non-stationary Dataset*: As EEG signal varies from time to time and session to session features of Human signal pattern becomes non stationary[9]

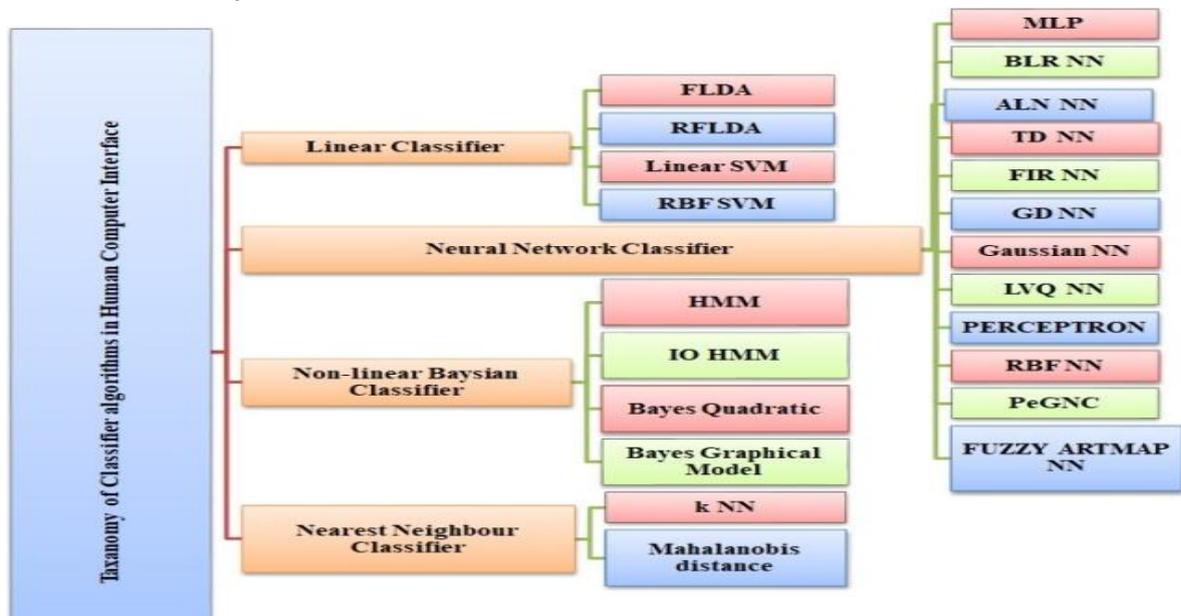


Fig. 4. Taxonomy diagram for Human Computer Interface Algorithms

The classification attempts to generate the output commands to execute the output of HCI application. The various classification algorithms are classified on the basis of various classifier properties as follows:

▪ *Linear Classifier Algorithms*: The functions used in a algorithms are Fisher’s and Regularized Fishers Linear

Discriminant Analysis (FLDA) and (RFLDA) for multiclass problems.[12,13] The most popular linear classifier is Support Vector Machine (SVM) due to various advantages[26].

▪ However, the selected hyperplane also maximize the margins to increase the training dataset point. whereas Gaussian or Radial Basis Function SVM (RBF SVM)[40,41].

▪ *Neural Network Classifier Algorithms:* Neural Network Classifier is a linear classifier but generation of nonlinear decision boundaries is the general principal of several artificial neurons[31]. The most popular Neural Network algorithm is Multilayer perceptron.[33]. It consist of several neuron layers, more than 1 hidden layers and one output layer.[49]. Therefore Multilayer Perceptron is also known as Perceptron which can deliver a linear, discriminant, static and stable features. Beside Perceptron many other Neural Network classifier algorithms are used like,(LVQ, Neural Network FIRNN, TDNN, GDNN, RBF BLRN, etc.  
 Non-linear Bayesian Classifier: The most common algorithms are Hidden Markov Model (HMM)and Bayes quadratic[4]. These algorithms are nonlinear, fast , static and unstable to produce decision boundaries. Bayesian classifier results into highest probability based on feature vectors. Bayes quadratic classifier follows Gaussian Distribution to lead to quadratic decision boundaries. Hidden Markov Modules (HMM) offers probability by witnessing the feature vector. It is nonlinear, discriminant, unstable and dynamic in nature. It works perfectly for time

series classification.

▪ *Nearest Neighbors Classifier:* This is the simple classifier working on the principal of nearest neighbours. It can follow the nearest distance measure using Mahalanobis distance and k cases from dataset for k-NN classifier. This is also non-linear, unstable generative and discriminant type of algorithms.

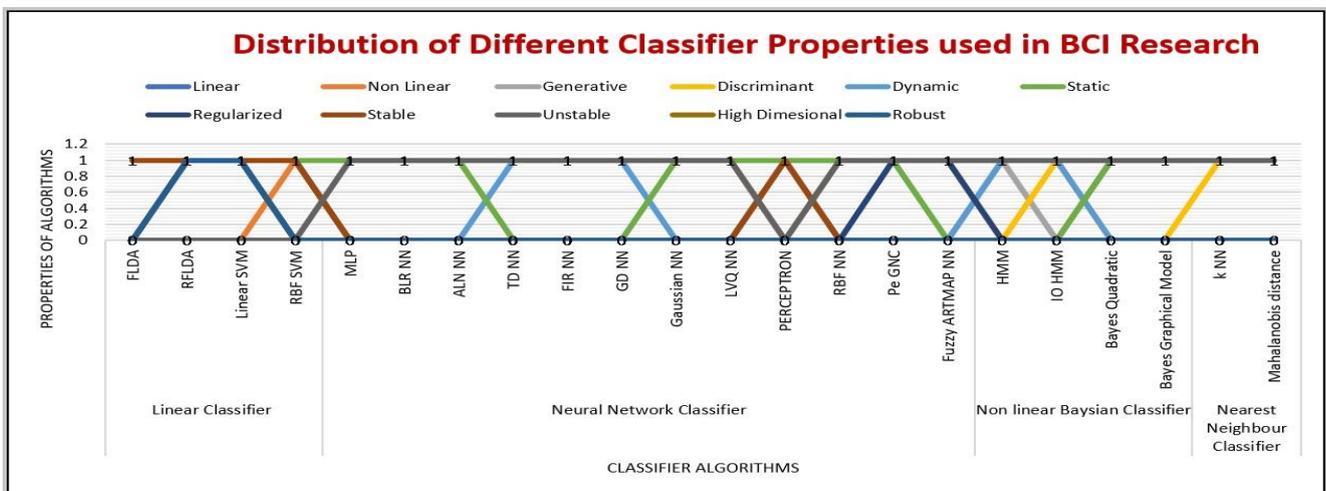
From the graphical distribution, we can easily analyses the various classifier algorithms with different properties to classify.

**IV. RESULT AND DISCUSSION**

The classification techniques are categorized under linear classifier, Nonlinear Bayesian Classifier, Neural Network Classifier and Nearest Neighbor Classifier. All these techniques are evaluated with properties like linear, nonlinear, generative, discriminant, dynamic, static, regularized, stable unstable high dimensional and robust. The Table I explains the various properties of different classification algorithms. The Fig.5. displays the Graphical Distribution of Classifier Properties for Different Algorithms and lastly the Table II explains the advantages and disadvantages of different classifier algorithms with the reference details.

**Table- I: Review study of different classification algorithms**

| Sr No | Properties       | Linear Classifier |       |            |         |     | Neural Network Classifier |        |       |        |       |             |        |            |        |        | Non linear Bayesian Classifier |     |        |                 |                       | Nearest Neighbour Classifier |                      |
|-------|------------------|-------------------|-------|------------|---------|-----|---------------------------|--------|-------|--------|-------|-------------|--------|------------|--------|--------|--------------------------------|-----|--------|-----------------|-----------------------|------------------------------|----------------------|
|       |                  | FLDA              | RFLDA | Linear SVM | RBF SVM | MLP | BLR NN                    | ALN NN | TD NN | FIR NN | GD NN | Gaussian NN | LVQ NN | PERCEPTRON | RBF NN | Pe GNC | Fuzzy ARTMAP NN                | HMM | IO HMM | Bayes Quadratic | Bayes Graphical Model | k NN                         | Mahalanobis distance |
| 1     | Linear           | Yes               | Yes   | Yes        |         |     |                           |        |       |        |       |             | Yes    |            |        |        |                                |     |        |                 |                       |                              |                      |
| 2     | Non Linear       |                   |       |            | Yes     | Yes | Yes                       | Yes    | Yes   | Yes    | Yes   | Yes         |        | Yes        | Yes    | Yes    | Yes                            | Yes | Yes    | Yes             | Yes                   | Yes                          | Yes                  |
| 3     | Generative       |                   |       |            |         |     |                           |        |       |        |       |             |        |            |        |        | Yes                            | Yes | Yes    | Yes             | Yes                   | Yes                          |                      |
| 4     | Discriminant     | Yes               | Yes   | Yes        | Yes     | Yes | Yes                       | Yes    | Yes   | Yes    | Yes   | Yes         | Yes    | Yes        | Yes    | Yes    |                                | Yes |        |                 | Yes                   | Yes                          |                      |
| 5     | Dynamic          |                   |       |            |         |     |                           | Yes    | Yes   | Yes    |       |             |        |            |        |        | Yes                            | Yes |        |                 |                       |                              |                      |
| 6     | Static           | Yes               | Yes   | Yes        | Yes     | Yes | Yes                       | Yes    |       |        | Yes   | Yes         | Yes    | Yes        | Yes    |        |                                |     | Yes    | Yes             | Yes                   | Yes                          |                      |
| 7     | Regularized      |                   | Yes   | Yes        | Yes     |     |                           |        |       |        |       |             |        |            | Yes    | Yes    |                                |     |        |                 |                       |                              |                      |
| 8     | Stable           | Yes               | Yes   | Yes        | Yes     |     |                           |        |       |        |       |             | Yes    |            |        |        |                                |     |        |                 |                       |                              |                      |
| 9     | Unstable         |                   |       |            |         | Yes | Yes                       | Yes    | Yes   | Yes    | Yes   | Yes         |        | Yes        | Yes    | Yes    | Yes                            | Yes | Yes    | Yes             | Yes                   | Yes                          |                      |
| 10    | High Dimensional |                   | Yes   | Yes        |         |     |                           |        |       |        |       |             |        |            |        |        |                                |     |        |                 |                       |                              |                      |
| 11    | Robust           |                   | Yes   | Yes        |         |     |                           |        |       |        |       |             |        |            |        |        |                                |     |        |                 |                       |                              |                      |



**Fig.5. Graphical**

**Table- II: Literature analysis of different classification algorithms**

| Classifier Type                | Algorithms            | Reference Paper                               | Advantages  | Disadvantages   |
|--------------------------------|-----------------------|---|---|---|
| Linear Classifier              | FLDA                  | GertPfurtscheller et al. 2000 Kuo et al. 2016 | Easy implementation with linear decision boundary and fast classification | Complex operations with matrices                              |
|                                | RFLDA                 | Alexander et al. 2000                         | Faster and more accurate classification                                   | More complex with gaussian assumptions training time          |
|                                | LINEAR SVM            | P.L.C. Rodrigues1 et al. 2017                 | Better accuracy with complex nonlinear data points                        | Computationally expensive                                     |
|                                | RBF SVM               | Ghanbari et al. 2014                          | Handles overfitting easily  | Time consuming Training process with multiple classes         |
| Neural Network Classifier      | MLP                   | Ghanbari et al. 2014                          | Low computation time  | feature have maximum variance                                 |
|                                | BLR NN                | Li, Y et al. 2014                             | Reduce problem complexity   | depends upon scaling of data                                  |
|                                | ALN NN                | Vladimir A. Maksimenko et al 2018             | Easy to use and implement   | learning process is slow                                      |
|                                | TD NN                 | Goyal et al. 2016                             | Data driven and self adaptive   | requires huge processing time                                 |
|                                | FIR NN                | Vladimir A. Maksimenko et al 2018             | high accuracy   | hardware complexity   |
|                                | GD NN                 | Kumar et al 2015                              | noise tolerance   | extensive memory requirements                                 |
|                                | Gaussian NN           | Fatemeh Safari et al 2010                     | easily identify complex relationsbetween variables                        | handles overfitting   |
|                                | LVQ NN                | Li, Y et al. 2014                             | Easy to use with less features  | difficult to know how many neurons and layers are necessary   |
|                                | PERCEPTRON            | Vladimir A. Maksimenko et al 2018             | Easy to implement   | slow learning   |
|                                | RBF NN                | Kumar et al 2015                              | Handles real life problems  | requires hardware to handle the real situations               |
|                                | PE GNC                | T. Felzer et al. 2003                         | efficient learning  | requires high processing time                                 |
|                                | FUZZY ARTMAP NN       | Fatemeh Safari et al 2010                     | handles uncertainty efficiently   | gives precise solutions                                       |
| Non-linear Bayesian Classifier | HMM                   | Hsu, W. et al 2015                            | freedom to manipulate the training and verification process               | large number of unstructured parameters                       |
|                                | IO HMM                | S. Chiappa et al. 2004                        | powerful modeling tool than statistical methods                           | unable to handle higher order correlation                     |
|                                | BAYES QUADRATIC       | Z. A. Keirn et al. 1996                       | suitable for small dataset  | sensitive to input data as all features are equally important |
|                                | BAYES GRAPHICAL MODEL | B. Blankertz et al. 2002                      | Prediction with tolerance to corelated input                              | Outliers existence with complex models                        |
| Nearest Neighbour Classifier   | KNN                   | B. Blankertz et al. 2002                      | Effective, Non-parametric, robust classifier                              | time consuming classifier with high computational cost        |
|                                | MANALOBBIES DISTANCE  | F. Cincotti et al. 2003                       | correlation among variables   | tends to overclassify   |

**V. CONCLUSIONS**

The overall finding of Human Computer Interface Applications, provides various classification techniques like linear non-linear static dynamic stable unstable etc. This paper studied the different techniques for classification based on the properties stable generalized robust and high dimensional. From table I and II it is observed that linear classifier linear classifier are easy to implement but distributed and stable . The neural network classifiers are more unstable and discriminant but more accurate. The nonlinear Bayesian networks are accurate for small dataset as they cannot handle the high dimensional dataset. Lastly the nearest neighbor classifier are convenient for nonparametric dataset as it provides robustness and generic data handling. Therefore , the use of classifier is completely depends on the application and its communication commands to be executed. The accuracy of executing commands depends on the accuracy of correctly used classifying classifier.

In the given review paper the study of various classification algorithm with brain signal patterns is done with focusing of different classifier taxonomy like linear-nonlinear feature extraction, generative -discriminative, Static-dynamic and stable-unstable with regularized performance. Similarly, the HCI system handles many increasing challenges in HCI applications.

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