An Improved Classification Architecture for Hand Gesture Electromyographic Data that Makes Use of Swarm Intelligence as a Feature Selection

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Abstract

Electromyography, often known as EMG, has become rather well-known for the contribution it has made to the overall architecture of the categorization of pain associated with a particular muscle or tissue. EMG is often employed both in the assessment of fitness professionals and in the course of the improvement of individuals who have physically difficult conditions. It is required to train a system using the EMG attribute set that is considered to be the most relevant in order to be able to identify EMG data in such a way that it is accurate with regard to any class. This research paper outlines an innovative design approach for enhancing the classification accuracy of the EMG signal as a whole (Rajeswari & Jagannath, 2017).

Keywords: EMG, ANN, MLP, SVM, LDA, and KNN.

1. Introduction:

EMG signals are one of the types of biomedical signals that provide important information that is vital in various clinical diagnoses, human-computer interaction systems dedicated to prosthetic devices, and security checks in controlled access areas. EMG signals are specifically used to monitor the signal which is fed at the input and converted into an electrical signal which is measured further. It is a tool that is used to identify neuromuscular diseases like multiple sclerosis, Huntington's, etc. EMG is a clinical technique that allows professionals to assess the activity of muscle tissues and neurovascular terminals. The assessment is based on their electrical level of physical activity. EMG instrument is a device that increases and captures the biophysical possibilities of the central nervous system. Recent digital technologies can capture even the smallest impulses, measure the frequency response of periods automatically, and do spectrum analysis on them. The device is a comprehensive software platform ability to record particular muscle tissue impulses (biopotentials). Bio potentials are enhanced with the gadget, allowing clinicians to detect the extent of muscle tissue injury without undergoing an invasive screening test. The system that analyses departures from the standard is equipped with a diode. The signal is generated by the device, and a representation of the condition of such heart muscle and nervous system of the abdominal region during examination is updated in real time. Older generation record the signals and analyse the collected signals on sheet, whereas modern technologies exhibit the input image on the panel. There have been numerous ways discovered for processing complex EMG signals that are aided by EMG classification using ANN, MLP, SVM, LDA, and KNN (Reaz et al., 2006). Daniel in early 1990's, started to search the possibilities in EMG signal analysis. In the procedure, he conducted several experiments over kids under 17 years to check whether the EMG analysis is applicable on all age groups or not.

Patient	Age	Sex	Clinical diagnosis	Muscle biopsy (age)	EMG (age)
1	16y10m	M	Duchenne muscular dystrophy	+ (3)	N/A
2	16y 4m	M	Duchenne muscular dystrophy	+ (5)	N/A
3	12y11m	M	Beckers dystrophy	+ (5)	N/A
4	12y 5m	F	Myotonic dystrophy	N/A	+ (7)
5	11y 5m	F	Mild myopathy	+* (11)	+
6	11y 0m	M	Duchenne muscular dystrophy	+ (5)	N/A
7	10y 9m	M	Duchenne muscular dystrophy	+ (3)	N/A
8	10y 7m	M	Duchenne muscular dystrophy	+ (5)	N/A
9	10y 3m	F	Dermatomyositis	N/A	+ (10)
10	10y 0m	M	Myotonic dystrophy	N/A	+ (3)
11	9y 6m	M	Duchenne muscular dystrophy	+ (8)	N/A
12	9y 3m	M	Duchenne muscular dystrophy	+ (5)	N/A
13	8y10m	M	Duchenne muscular dystrophy	N/A	N/A
14	8y 4m	M	Dermatomyositis	− (8)	+ (8)
15	7y 2m	M	Duchenne muscular dystrophy	+ (3½)	N/A
16	6y10m	F	Congenital myopathy	N/A	N/A

Figure **Error! No text of specified style in document.**.1 EMG Analysis over kids under 17 years

Surprisingly, the analysis was accurate and Daniel established the significance of EMG over any age group.The vital aspect of automated EMG interpretation and classification lies in the data acquisition, positioning of electrodes, and the technique (invasive or non-invasive) involved in EMG recording (Lozano-García et al., 2018) . EMG is usually obtained by putting sensors on the top layer of skin and recording the excitability. In contrast, invasive surgeries entail the insertion of electrodes beneath the skin. Surgical approaches allow sensors to be placed closer to muscular of importance, but they are less useful over average. Investigative approaches have also been demonstrated to create more trans heterogeneity and reduced reproducibility over time.

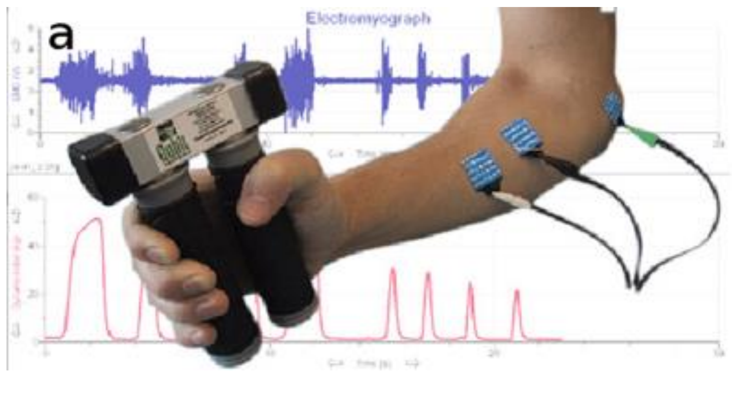

Figure **Error! No text of specified style in document.**.2 Invasive EMG Techniques

Machine Learning (ML) is an Artificial Intelligence-powered branch that arose from the necessity to educate systems how to model and simulate a response from a situation (Roy et al., 2020). Machine learning allows systems to programme themselves. It's utilised for everything from tedious work automation to providing intellectual insights. Without being particularly intended to forecast performance, the ML algorithm allows online services to be much more effective. In order to extract the information from any rule base, it must be trained with suitable information extracted from the data set as shown in Figure 1.1. The process is called data mining and it involves the training and the classification architecture.

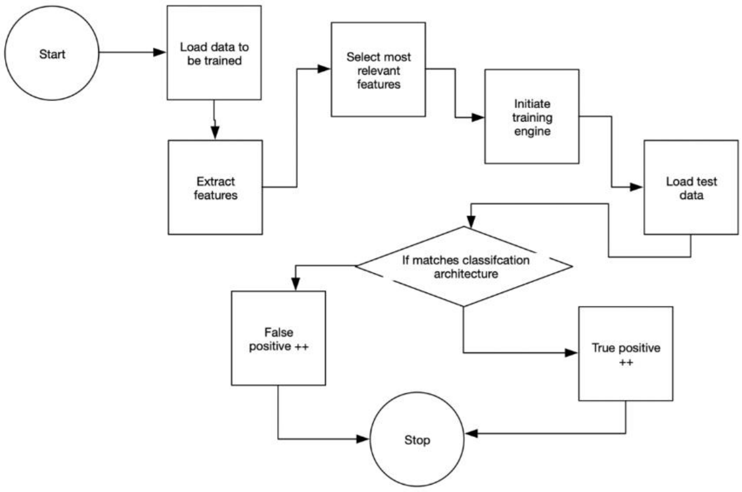

Figure **Error! No text of specified style in document.**.3 General training and classification architecture

2. Literature Review

Kaur et al. (2009), the authors presented a study based on the classification of elbow gestures and also applied feature extraction techniques. The author also provides the filtering of the EMG signals that is important to remove the noise from signals. Two types of feature extraction techniques are applied as; time and frequency domain. For the classification, K-NN algorithm has been implemented. The experimental outcomes show that the performance accuracy is achieved as 90% (Kaur et al., 2009).

Phinyomark et al. (2012) presented a work on using the feature extraction approaches. The author used different features specific to 37 domains and also presented the various properties of features. As seen in the result, it is concluded that the time domain features were having more redundancy. The mathematical property of the features was implemented for grouping into four types that are; prediction model, complexity, energy, and frequency. The work also recommended a viable technique to avoid the redundancy problem and signal classification (Phinyomark et al., 2012).

Küçük et al. (2013) introduced an EMG data named MUAPs' that consists healthy and Amyotrophic Lateral Sclerosis (ALS) disease subjects. For feature extraction, time and frequency domain features were applied that contain 10 feature vectors. Two classifiers were implemented; k-nearest neighbor (KNN) and SVM. The experimental results show that the

K-NN classifier performs better classification accuracy as compared to SVM (Küçük et al., 2013).

Artameeyanant et al. (2014) introduced an approach for feature extraction that transformed the complex network by applying a vertical visibility algorithm. The author applied SVM for classification. The signals are classified into three cases such as myopathy, neuropathy, and healthy. As the experimental results, the proposed work provides better accuracy but it is not suitable for extracting accurate features because of the variation of signals (Artameeyanant et al., 2014). Xue et al. (2014) had implemented PSO for the feature selection stage. They concluded that precise selection of relevant features using some optimization approaches would significantly revamp the classification accuracy of the EMG signal classification (Xue et al., 2014). Gokgoz & Subasi (2015) proposed DWT based technique to classify the features. In this framework, the EMG signals are automatically classified as ALS, Normal, and myopathy by applying algorithms and comparative analysis is performed to compute the classification accuracy as 96.67 % (Gokgoz & Subasi, 2015). Hamedi et al. (2015) proposed a multiclass least-square SVM classification that is based on the facial gestures. The RBF kernel provides the highest classification accuracy that is computed as 93%. The authors used the bipolar electrodes to analyze the gestures and facial states that are represented in ten different forms. The segmentation results using the RMS and classifier used to extract the features. The superiority of the model had been evaluated using the fuzzy technique and SVM method (Hamedi et al., 2015).

Zorarpacı and Özel (2016) had presented a hybrid approach for the features selection stage inspired by the Differential Evolution and Artificial Bee Colony (DEABC). The combination proved to successfully address the classification challenges raised at the feature selection stage during EMG signal Classification (Zorarpac\i & Özel, 2016).

Too et al. (2017) introduced a study that is applied to determine the performance of feature extraction using the LDA was introduced to investigate the performance evaluation of the extracted features. The results evaluation shows that the frequency domain features show better accuracy by applying the LDA classifier. The comparative analysis was conducted between the TD feature and FD feature with LDA, and it is computed that FD with LDA shows better results and computed accuracy is 91.34% (Too et al., 2017).

Toledo-Pérez et al. (2019) presented a detailed survey using EMG signal and SVM to classify the signal. The author gives a detailed discussion of several signals used, obtained accuracy, feature vector, and kernels that are used. This work also describes the number of signals that are applied for classification. Several studies included that are based on the SVM-based classification with the help of different tools for signal processing fields (Toledo-Pérez et al., 2019).

Khan et al. (2019) introduced a framework based on EMG signals denoising, feature extraction, and classifications. The author decomposed the signal for denoising, time and frequency domains applied to extract the features, and SVM and LR applied to classify the signal. The signals are recorded by a healthy individual or patient who was suffering from

ALS disease. The experimental results in terms of performance parameters such as; classification accuracy, specificity, F-measure, and area under the ROC curve (AVC). LR classification technique provides better results against classification accuracy that is computed as 95% (Khan et al., 2019).

Khan et al. (2021) presented a hand gesture-based system that is applied to recognize hand gestures by applying supervised learning. The researcher used normalization for EMD to segment the features. SVM classifier is implemented on EMG signals by using four types of hand gestures like wrist extension, wrist flexion, clenched, and resting hand. As discussed in the results, the machine learning model obtained higher classification accuracy that is 98.9%. This system helps handicapped people through non-verbal communication and physically challenged people through machine communication (Khan et al., 2021).

Hachemi et al. (2021) introduced an intelligent classification system that is applied to check flexion and extension based on EMG signals. In this work, firstly a simple single channel of EMG acquisition circuit is designed that is based on two metrics. The PCA was applied for evaluating and perform achievement as 100% rate of recognition using DWT (Hachemi et al., 2021).

EMG refers to the signal that is utilized in order to check the pain and movement in specific muscle (Subasi, 2012). As it has been illustrated earlier that the analysis of EMG includes the feature extraction, followed by training and classification mechanism. There are several areas of work for EMG data classification. Gesture classification has been observed to be prominent for the researchers in the last few years. Starting from elbow gesture, facial gestures hand gestures and limb classification have attained the most focus when it comes to EMG classification (Fajardo et al., 2021; Hamedi et al., 2015; Kaur et al., 2009; Khan et al., 2021; Mukhopadhyay & Samui, 2020). The problem of this research work is inspired by the work Fajardo that incorporates hand gesture classification for multiple hand gestures utilizing the validation using neural networks (Fajardo et al., 2021). The training architecture of gestures is completely dependent upon the data that is aggregated to process the information and the extracted features that are contributing in the judgement formation. The gesture features are classified into two categories namely the time domain and the frequency domain feature (Fajardo et al., 2021). Both category features are enormously important for the appropriate training of the data against its dignified label. It has been concluded from the written literature that all the extracted features could not be important based on the type of EMG that is getting processed and hence a feature selection algorithm must be incorporated in between the training and data collection (Alkan & Günay, 2012; Mishra et al., 2016). The feature selection architecture involves the establishment of the correlation among the features in order to provide significant bonding among the attributes that has been passed for the training and the classification. There are several ways of establishment of the co-relation among the feature set. It is evident from the literature that, machine learning algorithms have made a mark when it comes to selecting the features of any category or architecture (Zakeri & Hokmabadi, 2019). The preciseness of the feature selection algorithm decides the potential of the classification accuracy (Márquez-Figueroa et al., 2020). Swarm Intelligence (SI) have been observed to use quite frequently in the selection procedure whether it is feature or feature set selection. SI has gained a lot of variations when it comes to modifying the behavior of the existing Swarm Algorithm. Utilization of wolf Optimization, Artificial Bee Colony (ABC) and PSO have been frequent in recent years (Jha et al., 2019; Kan et al., 2020; Kumar et al., 2007; Shehab et al., 2020). As the training pattern remains fixed for most of the parts of the classification, the most possible modification has been observed in feature selection and alteration in the policy of the feature selection depending upon the dataset. The possibilities in the advancements of the optimization algorithm are endless and hence, the problem of this research work is to be derived in two phase. The first phase aims to select the most relevant features using SI algorithm architecture. The problem extends to design a novel fitness function that adapts the behavioral changes of the data so that it can be applied to multiple datasets. The second phase of the problem statement extends to train and classify the optimized dataset for maximum utility and efficiency. The problem formulation also extends to evaluate and compare quantitative parameters for the comparison of the proposed algorithm with other state of art techniques.

3. Objectives

Based on the illustrations that has been made in the problem formu8lation and the introduction section and, the contributions made in the gap, the following objectives have been finalized.

a) To study and analyze machine learning oriented feature selection algorithm and classification algorithms for hand gestures classification through EMG.
b) To design an improved machine learning feature selection algorithm inspired by Swarm Intelligence (SI) for hand gesture classification.
c) To train and classify the extracted and selected features against the provided dataset ground truth values of hand gesture using deep neural networks.
d) To evaluate and compare the quantitative parameters of the proposed algorithm with state of art techniques for hand gesture.

4. Hypothesis

The problem formulation is based on the enhancement of the selection procedure of the features for precise classification. Based on the studied literature and observed facts illustrated in problem statement, the following hypothesis has been formed.

Null-H0: There is no significant difference in the overall classification accuracy after application of feature selection method in hand gesture EMG data classification.

Alternate -H1: Reverse to H0

Null -H2: The overall classification score is independent upon the segments and type of features in hand gesture EMG

Alternate -H3: Reverse to H2

Proposed Work:

5. Research Design

The proposed methodology aims to increase the overall class accuracy of the proposed algorithm against the provided ground truth value as the hand gestures. The classification accuracy depends upon the accurate number of identified elements against its actual ground truth value, it becomes vital to select appropriate features for the processing. It has been already briefed in the introduction section that hand gesture EMG signal has both time and frequency domain features. The time domain features are the features that extracted directly from the hand gesture EMG signal itself whereas the frequency domain features are the features that are extracted by the decomposition of the signal. The proposed work is divided into two phases namely the feature selection and the training and classification phase. The training phase aims to optimize the feature selection process by applying SI to it whereas the classification process takes the test data and processes it against the trained repository created in the feature selection phase.

5.1 The feature selection

The training phase has a lot of responsibilities that has to be attained and are shown in Figure 4.1. The preliminary work of the proposed algorithm is to clean the data which will involve two steps namely the Not a Number (NaN) and missing values. A signal gets missing values when the attached from sensor fails to record the measurement due to any physical or technical fault as shown in Figure 4.1.The preprocessing will be followed by feature extraction and feature optimization process. As illustrated earlier also, two different feature domains will be applied namely the time domain and the frequency domain.

The time domain features will collectively hold those features that represents statistical evaluation of the data. As for example, the time domain features will have MSE, SE, Entropy etc. and are disused in the introduction section as well. The frequency domain features will have decomposition-based features that will be extracted from the decomposition of the provided data. As observed in the related work section, there are several decomposition methods that can be applied for the same and are illustrated in Figure 4.1.

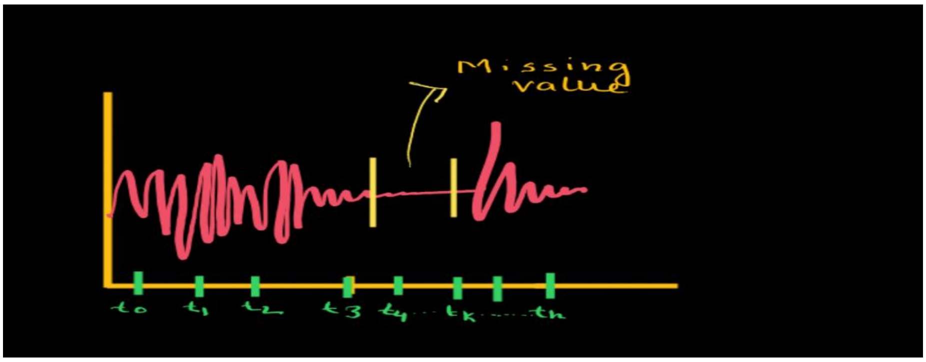

Figure **Error! No text of specified style in document.**.4 The missing value case

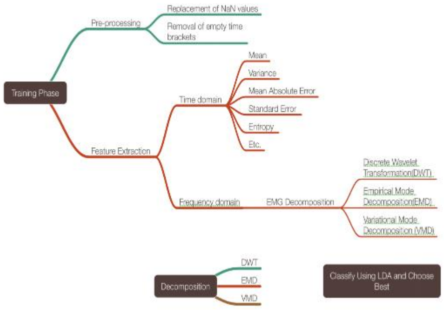

Figure **Error! No text of specified style in document.**.5 Work flow

The proposed algorithm will apply an LDA based validation mechanism to select the best possible decomposition method (Fajardo et al., 2021) The proposed algorithm puts its first enhancement when the features have been extracted and that is illustrated in the work flow shown in Figure 4.2. In order to perform the training, the training algorithm preliminarily requires data to be processed. In case of proposed work scenario, there are two different repositories that can be considered for the evaluation namely Kaggle and UCI machine learning. As for example, Figure 4.3 represents the EMG data with 7 ground truth values in the repository (Electromyography(EMG) Dataset | Kaggle, 2019). Ground truth is the base class of the data and all the features are trained against its specific class.

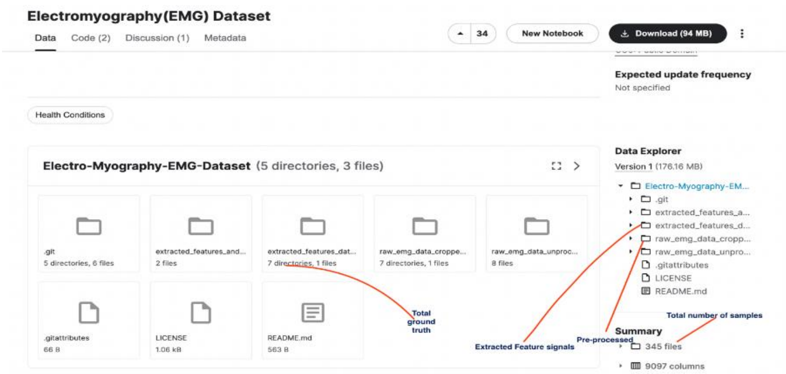

Figure **Error! No text of specified style in document.**.6 Kaggle repository data with 7 ground truth classes (Electromyography(EMG) Dataset | Kaggle, 2019)

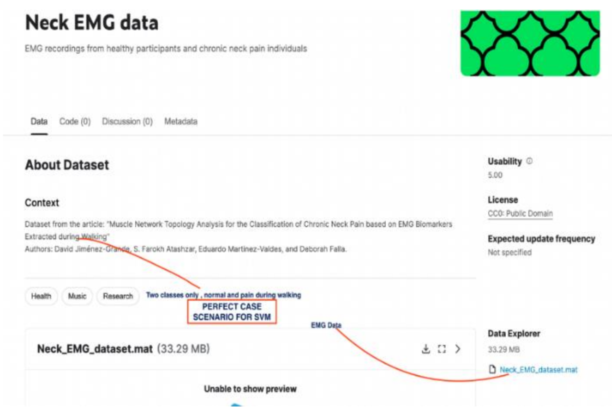

Figure **Error! No text of specified style in document.**.7 Kaggle repository data with 2 ground truth classes

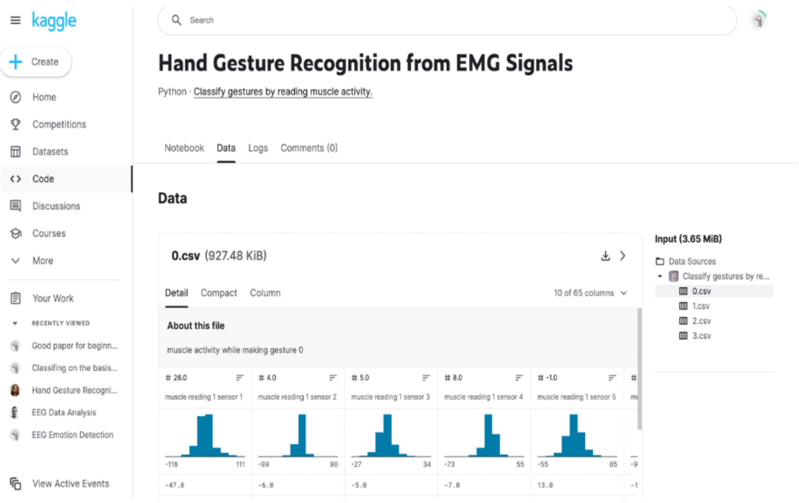

Figure **Error! No text of specified style in document.**.8 Kaggle repository data for hand gesture classification

5.2 Swarm Intelligence

Swarm Intelligence(SI) is a subsection of meta-heuristic algorithm series that follows statistical machine learning architecture. Any SI algorithm will require the following elements

a) The working identities
b) The selectors
c) The evaluation method

The working identities are the identities that bring food to the table. SI is bascially based on food collection behaviour of different species in the world. SI was first proposed in 1991 till date, a lot of modifications and alterations have been presented till date (Parpinelli & Lopes, 2011).

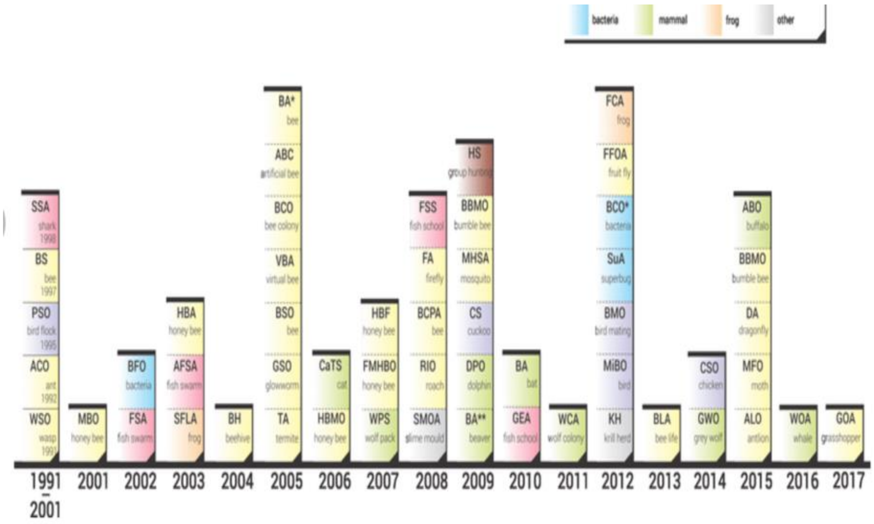

Figure **Error! No text of specified style in document.**.9: SI algorithm list (Parpinelli & Lopes, 2011)

SI algorithm works on the base of co-relations that brings out the attention of the evaluation. As for example, in case of Artificial Bee Colony(ABC) algorithm, the employed bees are grouped together with other bees to form a search space and are evaluated by the onlooker bees. In the similar fashion, in case of Cuckoo Search (CS) algorithm, the cuckoo bird selects the nest of other host bird based on the maximum co-relation between the egg of the cuckoo bird and the egg of the other host bird. In the similar fashion, the newly proposed grass hopper algorithm creates its swarm with other hoppers that are near byin its exploitation phase and with other hoppers that are away from the hopper in the exploration phase (Abidin & Ismail, 2020; Qin et al., 2021). The general selection architecture of SI oriented architecture can be illustrated using the following work diagram.

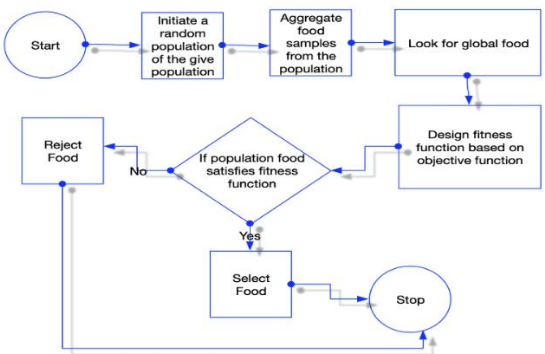

Figure **Error! No text of specified style in document.**.10 General Flow architecture of SI algorithm

Out of this algorithm list, Grass hopper was proposed in 2017 and further algorithmic archtiecture has been developed to the best knowledge by the time the document was written. The training architecture involves a random population selection that forms a swarm in search of food. A global food value is used which belongs to the entire population of the system. Once the features are selected, it would be supplied to Deep Neural Network (DNN) for the training (Merletti & Cerone, 2020; Zhang et al., 2019; Zhou et al., 2009). The training and classification is explained in the next section. In addition to that, the overall work flow will be as demonstrated in Figure 4.9.

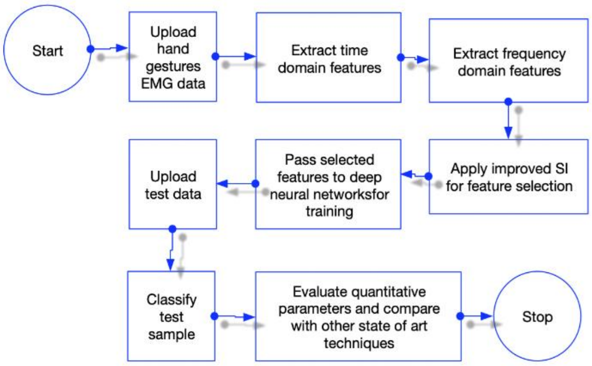

Figure **Error! No text of specified style in document.**.11 The general flow architecture

a. Training and Classification

The training and classification model in case of proposed work, utilized DNN due to several factors. The computation complexity of DNN is much less than that of Convolution Neural Networks (CNN) which was preliminarily designed for image processing. The data requirement of DNN is less than that of CNN. The training and classification section will take the input from the previous section in terms of two elements namely the selected feature vector and its original ground truth as shown in Figure 4.8.

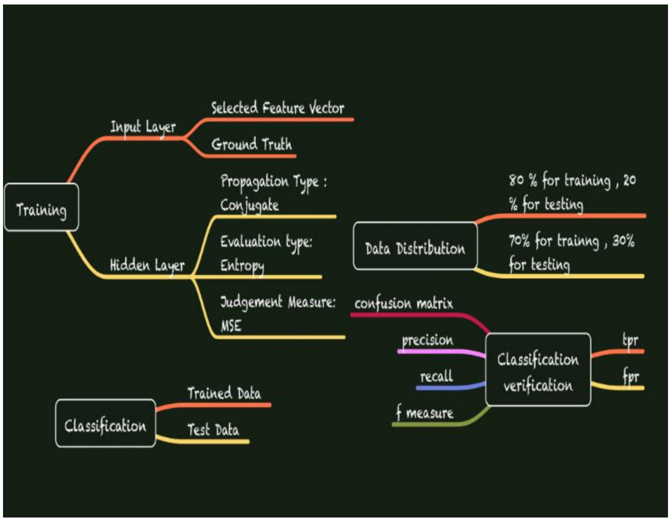

Figure **Error! No text of specified style in document.**.12 The distribution architecture

The training and classification architecture uses the extracted features after the selected from the hand gesture repository as input. To evaluate the performance of the proposed algorithm, a data distribution of 70-30 % viz. 70% data for the training and the rest of the data will be used for the classification architecture, will be adopted at the first glance. Later on, the 80-20 distribution can also be opted to check the performance of the proposed algorithm. The training engine will have input layer, hidden layer and the output layer. The hidden layer will propagate the data to understand the best co-variance in the data against the supplied ground truth hand gesture values. As shown in Figure 4.10, the judgement parameter is Mean Squared Error (MSE). Judgement parameter refers to the stopping criteria of the training engine. Various training engine utilizes various stopping criteria parameter such variance or standard deviation but MSE is one of the most common judgement parameters. The classification accuracy of will be evaluated using true positive (tp), false positive (fp), true negative (tn) and false negative (fn). Other than classification accuracy, precision, recall, f-measure and confusion matrix along with true positive rate (tpr) and false positive rate (fpr) will be common measures of evaluation.

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