World Academy of Science, Engineering and Technology
International Journal of Biomedical and Biological Engineering
Vol:12, No:10, 2018

Unstructured-Data Content Search Based on Optimized EEG Signal Processing and Multi-Objective Feature Extraction

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***Abstract*—**Over the last few years, the amount of data available on the globe has been increased rapidly. This came up with the emergence of recent concepts, such as the big data and the Internet of Things, which have furnished a suitable solution for the availability of data all over the world. However, managing this massive amount of data remains a challenge due to their large verity of types and distribution. Therefore, locating the required file particularly from the first trial turned to be a not easy task, due to the large similarities of names for different files distributed on the web. Consequently, the accuracy and speed of search have been negatively affected. This work presents a method using Electroencephalography signals to locate the files based on their contents. Giving the concept of natural mind waves processing, this work analyses the mind wave signals of different people, analyzing them and extracting their most appropriate features using multi-objective metaheuristic algorithm, and then classifying them using artificial neural network to distinguish among files with similar names. The aim of this work is to provide the ability to find the files based on their contents using human thoughts only. Implementing this approach and testing it on real people proved its ability to find the desired files accurately within noticeably shorter time and retrieve them as a first choice for the user.

***Keywords*—**Artificial intelligence, data contents search, human active memory, mind wave, multi-objective optimization.

I. Introduction

THE emergence of the modern concepts of the Internet of Things (IoT), Cloud Computing and Big-data, increased the complexity of data searching processes. However, users who look for specific information may spend relatively longer time looking at useless alternatives or trying different keywords. While the same word may refer to different objects, consequently, increases the average searching time [1]. For instance, if a user searches for an actor, but does not know his name, he/she might think of searching with a movie name. However, this will results with a long list, while the desired one might not be in it, until the user conducts several search trials. To tackle this problem, this work proposes a solution using the user's mindwave signal (Thoughts only) to reach the specific item directly and accurately.

Whilst several works attempted to use Electroencephalography (EEG) signal to comprehend human behavior amid the search process [2], [3], this work conducts the entire search process using human thoughts only. This work focuses on words pointed to images, not to texts or articles, while these words mostly have different cases.

In this work, EEG dataset is obtained from a number of volunteers, using NeuroSky Mindwave Mobile+ sensor [4]. Then, the Multi-Objective Artificial Bee Colony (MOABC) algorithm [5] is utilized to define the optimal features to be processed. Hereafter, the dataset is clustered using Feedforward Artificial Neural Network (FFN) algorithm [6]. To validate the effectiveness of the proposed system, real experiments were conducted by a focus group, showing enhanced results in terms of accuracy and delay.

Being a part of the VisualThoughts project by ATIT to build a real Natural Mindwave Processing (NMP) system, this work aims to constitute an initial paradigm for an entire NMP system connected to Natural Language Processing (NLP) systems, to provide a real-time visualization of human thoughts that may reflect on solving several problems in different aspects of human life.

The primary objectives of this work are to build an accurate EEG dataset for the predefined images, moreover, to define the most optimal features to be utilized in order to cluster this and other mindwave datasets. The approach proposed in this work provides an accurate and fast search for the data, not only using keywords but also based on their contents, using the imaginary thinking of the user through mindwave signals. However, this work is limited to the EEG query identification, without concentrating on the database retrieval processes. On the other hand, this work contributes to the literature by providing a simple, efficient and easy to use tool that can interpret mindwave signals from the forehead region only and apply it to data science. Moreover, it is able to identify the data based on their contents using mindwave signals only, with a wearable and easy to use device. In addition to that, this work introduces the totally genuine NMP field for the first time, including the memory and thoughts visualization processes.

This work tries to answer the following key questions: Is it feasible to retrieve the data based on its contents using mindwave signals only? and how?

Although this work revolves around the NMP, first presented in this work, it focuses only on the search part. However, the following section illustrates the preliminary background concepts. After that, the third section discusses the used methodology and design phases and parameters. The

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implementation process along with the results is discussed in the fourth section. With some enhancements briefed in the fifth section, finally, yet importantly, the sixth section summarizes the entire work and draws conclusions.

II. Preliminaries

Understanding human's way of thinking was a dilemma to psychologists and philosophers from the ancient time. For instance, Freud compared between the ego and the id as a relation between the rider and the horse [7]. This comparison was a direct allusion to Plato's description for the horse and rider, as the horse is the origin of the energy and the rider who determines the goal of movements [8]. However, modern science found that the two components (Emotional brain and rational brain) of human thinking and decision-making are dependent on each other. This was explained in Goleman's writings mentioned in [9], [10], where he explained the responsibility of emotions as the source that assists in making humans pay attention at the moment, where it is urgent. Moreover, provides an immediate action plan, without wasting time in double thinking, concluding that the emotional component evolved very early, and its response can take over the rest of the brain in a millisecond if threatened.

The emotional brain is particularly valuable at helping humans settle on hard choices. Its huge computational force, in addition to its capacity to process a huge amount of data in a parallel mechanism, guarantees that humans can investigate all the pertinent data while evaluating options at the same time. Big data are separated into sensible pieces, which are then interpreted into practical emotions. The reason these feelings are so shrewd is that they have figured out how to transform botches into instructive occasions. Humans are continually learning by experience, regardless of the possibility that they are not intentionally mindful of the advantages. It does not make a difference in the field of skill or experience, the brain dependably takes similarly, aggregating shrewdness through mistake [11].

The pivotal significance of human's feelings, due to the way that humans cannot settle on choices without them repudiates the ordinary perspective of human instinct, with its antiquated philosophical roots. For the majority of the twentieth century [12], the perfect of rationality was bolstered by logical portrayals of human life structures. The mind was imagined as comprising of four separate layers, stacked in ascending order of multifaceted nature. (The cortex resembled an archeological site: the more profound you burrowed the more remote back in time you voyaged).

Scientists clarified the life structures of the human mind as in [13]-[15]: At its base was the brainstem, which represented the most fundamental real capacities. It controlled pulse, breathing, and body temperature. Over that was the diencephalon, which managed hunger strings and rest cycles. At that point came the limbic region, which created human feelings. It was the wellspring of desire, viciousness, and indiscreet conduct. (Individuals imparted these three cerebrum layers to each other well-evolved creature). Finally, there was the sublime frontal cortex—the perfect work of art of advancement, which was in charge of reason, insight, and ethical quality.

The thinking parts of these components are the limbic region and the frontal cortex, which represents the emotional and rational brains, more details in [16], [17].

The EEG signals of those parts may be sensed using several kinds of sensors, so as to display the medical status of the mind as well as to examine its behavior. In this work, NeuroSky Mindwave mobile+ sensor is used, with the intention to sense the mindwave signals associated with the user's thoughts.

This sensor [4], which is a wearable and easy to use gadget, looks like a headset, and able to measure numerous emotional and thinking states using one sensor only. This sensor, which is positioned at the user's forehead whilst wearing the headset, outputs the attention status, Eyeblink, Meditation level, mindwave bands and other raw data, measured through its EEG sensor.

EEG signals represent the process of recording mindwave activities, by means of positioning sensors on the user's head, these activities are commonly neurotransmitters associated with some processes inside the human's mind. Those signals typically measured in Hertz (Hz) are labeled into bands, primarily based on their speed, can be grouped into slow, mild and fast mindwaves. Table I, clarifies those bands with their related waves [18].

This selected sensor can measure those waves from the forehead region. It reads the tiny voltage difference of each wave, amplifies it around 8000 times to improve any faint EEG signal, then filters it in the frequency domain and in the time domain with low and high pass filters to preserve the signals among 1Hz to 50 Hz. Then the maintained signals are sampled at 512Hz. and then, the signal is monitored within the frequency domain and the time domain in an effort to restore it against any artifact or noise. After that, it decodes the resulted signal right into a numerical value and sends it to the computer through Bluetooth.

TABLE I
Mindwave Signals and Their Description

Band	Mindwave	Signal (Hz)	Description
Infra-low	Infra-low	< 0.5	Slow Cortical Potentials.
Low	Delta	0.5-3	Produced in dreamless sleep and deep meditation. It is the source of empathy.
Moderate	Theta	3-8	The gateway to learning, intuition, imaginary, memory and information beyond conscious.
Moderate	Alpha	8-12	Define the present moment; learn alertness calmness, mind-body integration.
Fast	Beta	12-38	Decision-making, awareness, engagement in activity.
Fas	Gamma	38-42	Love, altruism

The above table shows the bands with their corresponding mindwaves and signals. As shown in the table, every mindwave sign has its own functionality and represents special task or occasionally represents the same task but from a different view.

After having sufficient background about the area under study and its components, the following section discusses the steps of the methodology followed for constructing the proposed design with a view to have the proposed solution implemented efficiently.

III. Methodology

A sample of the used sensor's output is illustrated in Figs. 1 and 2, demonstrating the average values of the 15 features for 10 trials by one volunteer thinking of one image. Due to brain's involvement in various tasks amid the trial, the attributes' values vary rapidly. Consequently, defining the required attributes for the processing phase is an optimization problem. Thus, MOABC is adopted to define the optimal features; moreover, FFN is utilized to classify them with their corresponding images.

Fig. 3 illustrates the primary stages of the proposed approach, which is comprised of data collection using EEG mindwave sensor, so as to be pre-processed to ensure its consistency. After that, the most optimal features are extracted using MOABC algorithm, and then the selected features are normalized in order to suit the FFN algorithm in the classification phase. The output of the classification phase is inversely normalized with a purpose to be used in building the database.

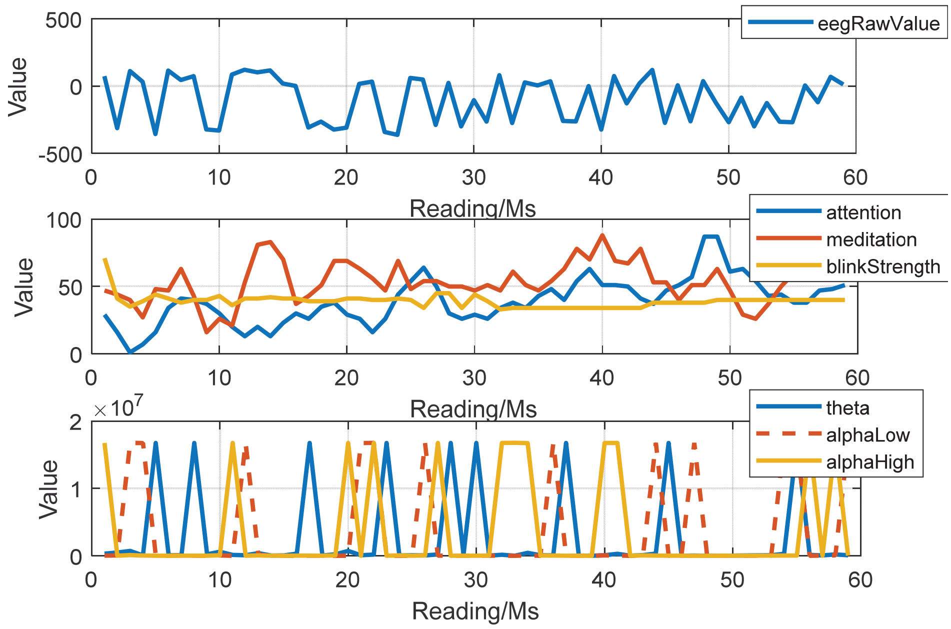

Fig. 1 Mind wave features (EEG Raw, Attention, Meditation, Blink Strength, Theta, Alpha-Low, Alpha-High)

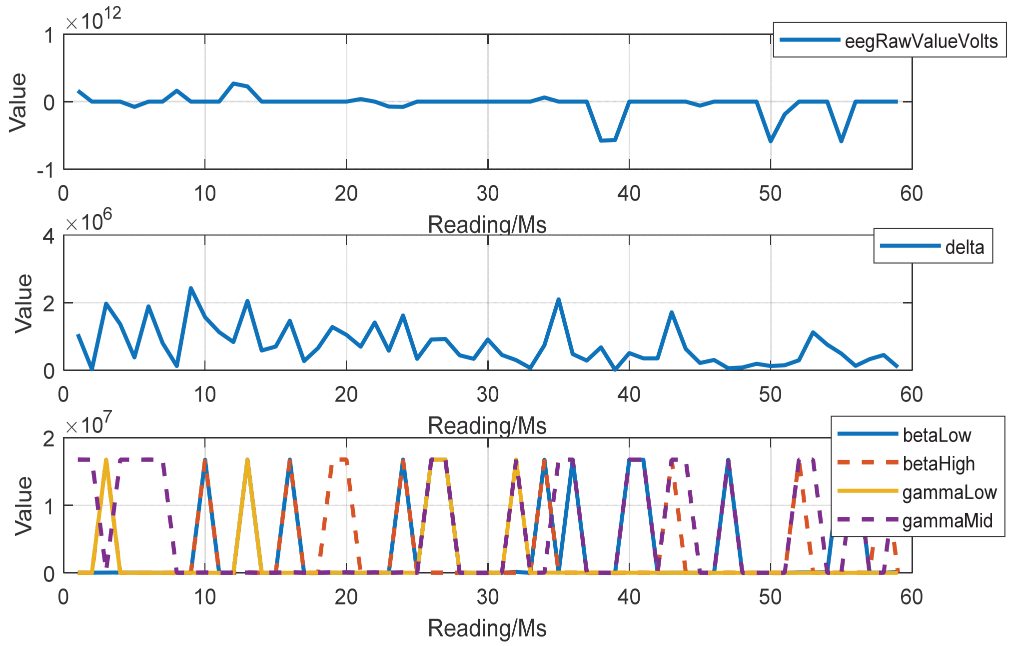

Fig. 2 Mind wave features (EEG Raw Value Volts, Delta, Beta-Low, Beta-High, Gamma-Low, Gamma-High)

Fig. 3 Proposed Approach Phases

A. Data Collection

To collect the EEG samples, the focus group of 15 persons (7 males, and 8 females), between 18 and 55 years old, are taken to a dark room, where a data-show projecting 4 different photos for each word case titled with its name, to be stored in the volunteer's unconscious mind. The dataset was collected by means of mounting the NeuroSky MindWave mobile+ sensor on the head of every individual person of the focus group. Then, they have been instructed to think about every case of each word for 60 seconds, to guarantee their attention. This was carried out three times a day (Morning, Afternoon, and night) for three non-consecutive days (Sunday, Tuesday, and Thursday). Moreover, the surrounding noise was not tuned, so random surrounding noise was taken from the real surrounding environment. This procedure was followed to generalize the samples, to provide random mental, physical, and external status by means of:

1- Including various mental status within the collected samples.
2- Including numerous physical status.
3- Including various external disturbances.
4- Including different ages.
5- Moreover, avoiding false readings or false thoughts from having an excessive influence on the results.

Although, this procedure continued until each volunteer completed thinking of all of the 10 predefined words, passing all of their cases.

The selected words and their cases are stated in Table II; those words normally confuse the web search engines and do not generally appear on top of the search results due to the variety of their use in different aspects. Whilst, there have been several different images for each case used in this project, in an effort to pre-program the thoughts of the volunteers.

As shown in this table, a large ratio of the words nowadays refer to different elements; subsequently, when searching out each one of them in any search engine, the desired choice might not appear on top or even on the first results page most of the times, specifically when using short terms or notations. For instance, *AUC* stands for the *Area under ROC Curve*, and additionally for the *American University in Cairo*, and such a lot of other things. While looking for this term in its first meaning, it is too difficult to be able to locate it within the first 10 pages, even using Google, which is the most powerful search engine. All in all, in the extent of retrieving the required choice quickly, users are required to add more keywords to their search, which in most of the situations are not applicable. This issue has worsened at the emerged era of big-data and IoT.

Considering this difficulty, it is been observed that users who search for any information on the web or any database, usually think about the desired information and imagine it in their mind. As a result, while matching this imagination with the corresponding information on the database, the consequences can be retrieved quickly, accurately as a first choice.

TABLE II
SELECTED WORDS AND THEIR MAIN CASES

Number	Word	Cases
1	Petra	Ancient Site, Factory, News Agency, University
2	Philadelphia	Ancient Site, city, Organization, University
3	Lincoln	Name, University, Car brand, City
4	Georgia	Country, US State, Name, Organization
5	Agora	Ancient city, Learning hub, Movie, Organization
6	Jordan	Country, River, Family, Athlete
7	Uranus	Planet, Greek god, Town, Organization
8	Monte Carlo	Principality, Radio, Simulation Algorithm, Organization
9	Bosporus	Strait, Garden, City, Organisation,
10	Alexandria	City in Egypt, City in Greece, Ancient City, Library

In this proposed model, the sample of words with their different cases was selected as input and large samples of their corresponding images have been used as output for the search system.

B. Preprocessing and Features Extraction

After collecting the dataset, it was pre-processed by removing the null and NaN values, which occurred due to some data connection loss between the Bluetooth transmitter antenna of the sensor and the Bluetooth receiver antenna of the computer, though, within the entire collected dataset, there were only 7 rows containing null or NaN values, which indicates that the connection was mostly stable, yet, those rows have been eliminated entirely from the dataset.

After that, the data were tested for outliers, simply by plotting the rows of each accumulated samples in the time domain as well as the frequency domain, a good way to ensure that no outlier element is available in both domains, accordingly as the data transferred by the FFN algorithm, it is going to be consistent. nonetheless, no outliers had been detected in the collected dataset for both domains, which means that that the data collection technique was reliable and accurate.

After cleaning the data, they have been normalized using (1) in order to map them from the current shape to a uniform shape, with a mean of 0 and a standard deviation of 1.

$$y = (x - \bar{x}) * \left(\frac{\sigma_y}{\sigma_x}\right) + \bar{y} \quad (1)$$

While y is the resulted row of normalized data, x is the row of data with its original shape, $\sigma_y$and $\bar{y}$ is the target standard diviation and mean of the data, respectively, after normalizing it, $\sigma_x$and $\bar{x}$ is the current standard deviation and mean of the data, respectively.

This allows the training function of the FFN to converge to the optimal values of weights and bias quickly and smoothly, by minimizing the Mean Square Error (MSE) function. This process, not only provides fast convergence for the FFN but also more accurate results.

After preparing the dataset, it becomes ready for the features extraction process. Hence, the used EEG sensor outputs 15 attributes, which are considered as features, using all of them can diverge the FFN due to the fact that some of these attributes contain relatively useless data. Therefore, it is required to define the attributes of interest accurately, which are the optimal attributes that contain the most useful data representing the thoughts of the user. This process can be defined as *optimization the features*, which is comprised of identifying the most superior features to be utilized by the FFN as a way to allow it to be converged quickly and provide the most accurate outputs.

So as to outline the most optimal features, an optimization algorithm needs to be used, but on the other hand, understanding the available features, it can be noticed that the selected features need to be taken into consideration dependently, and cannot be tackled separately, because the useful features representing the same information but from different channels. For that reason, the selected optimization algorithm should be able to output multiple dependent solutions accordingly; a multi-objective optimization algorithm is required. At the same time, there are different types of optimization algorithms that optimize multi-objective problems, with various behaviors in terms of speed and accuracy.

In this work, the trade-off process of selecting the most suitable algorithm considered the accuracy term only, as speed has lower priority, due to the fact that the features optimization process is required to be executed one time only, and will not return to it again. As a result, once identified, the same features will be used in the training, testing and at any time this proposed application is used.

Numerous multi-objective optimization algorithms were compared together using different multi-modal benchmark functions, following several criteria. Afterward, when calculating the mean results, MOABC algorithm was observed to be the most accurate one of them, minimizing the benchmark functions to zero in most of the instances and sometimes to values very near to zero.

Accordingly, in this work, the MOABC is adopted to select the optimal number and types of features. The processes of the MOABC algorithm, after its adaptation to suit the requirements of this identified problem, are illustrated in Algorithm I.

Moreover, the cost function of MOABC was built entirely using FFN algorithm, as illustrated in Algorithm II, such that the selected solutions by the MOABC particles are sent to the cost function. Where the FFN is trained on them and then MSE is calculated to compare the FFN output with the required target. After that, the value of the MSE is returned back to the MOABC to determine the next solution.

C. Classification

An initial step in the classification phase is to build a code table pointing to each image in the database, as the processing algorithm cannot process images in their original form. Accordingly, the codes used in this table are constituted of sequential integer decimal numbers from 1 to N, while N is the number of used imaged for all the cases. Doing this, the inputs, which are the mindwave features and the target, which is the code table, become ready for the processing phase. And hence, this problem has input and target, a supervised algorithm is required to be used. Consequently, in this work, FFN is used to classify the features with their corresponding images.

However, as this proposed technique uses FFN as a cost function for the MOABC, as stated in Algorithms I and II, this design results in two objectives at the same time. Hence, after implementing the entire system and accomplishing the best value for the cost function, the system then provides an accurate identification for the most optimal features to be used, with their samples classified accurately to their corresponding images.

The used settings for MOABC and FFN are illustrated in Table III. Using these settings, the proposed model identified three features only, to be the most optimal features, representing the thoughts of the users, which are Meditation, Alpha-high, and Theta, so as to be used henceforth to identify the user's request accurately.

Algorithm I: MOABC Algorithm

```
Start;
Define Features Dimension;
Generate Features Randomly;
Evaluate Features by Cost Function;
While (Cost Function not Minimized){
    Select New Features;
    Evaluate Features by Cost Function;
    If (All Particles Distributed?) {
        Store Best Selected Features;
            Store Best Cost Values;
        else{
            Distribute Particles to New Features;
            }
        }
        Update Best Features;
}
Optimal Features Defined;
```

Algorithm II: FFN Algorithm (Cost Function)

```
Start;
Build FFN;
Define Input and Target;
Define Random Weight and Bias Values;
While (Stopping Criteria not Met){
    Train FFN;
    Calculate MSE;
    Update Weight and Bias Values;
}
Store Weight and Bias Values;
Return MSE Best Value;
```

TABLE III
MOABC AND FFN ALGORITHMS SETTINGS

Modified MOABC Settings		ANN Settings	
Parameter	Value	Parameter	Value
Cost Function	'ANN_Cost_Fun'	Hidden Layer Neurons	55
Number of Variables	3	Transfer Function	'TANSIG'
Minimum Variable	1	Training Function	'Levenberg-Marquardt backpropagation'
Maximum Variable	15	Adaption Learning Function	'LEARNGDM'
Maximum Iterations	250	Performance Function	Mean Square Error
Number of Population	300	Epochs	500
Number of Onlookers	'nPop'		

After completing the clustering phase, the resulted output of the FFN is inversely normalized, in order to clarify its results. Finally, having defined the optimal features in addition to the optimal weights and bias values that minimized the MSE function, these values were saved in order to be used in the testing phase and in the application as a close box. The application system is illustrated in Fig. 4.

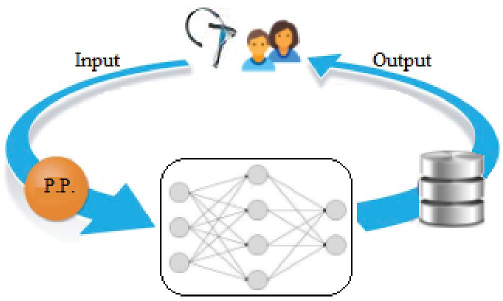

Fig. 4 Application System Components (P.P: Pre-Processing)

D. Building the Database

In this phase, the images were stored in the database server with their corresponding codes. Similarly, in large environments, the data, which is probably in different shapes and sizes, can be distributed in different servers on the cloud. Even though, the system will function in the same manner, as described in Fig. 4.

Initially, the user thinks about the data to look for, then the mindwave signals are transferred to the system, to take the Meditation, Alpha-high, and Theta features only. Then it preprocesses them and transfers them to the FFN engine, which identifies their corresponding code and sends it to the database to match the corresponding data (i.e. image) and retrieve it to the user.

IV. IMPLEMENTATION AND RESULTS

After implementing the proposed model, MOABC-FFN determined the optimal number of features. However, as shown in Fig. 5, using the optimal features (Meditation, Alpha-high, and Theta), the lowest mean cost function value of 4.13×10^{-4} is reached. They are used in the proposed model over all the conducted tests.

The convergence curve of the MOABC for the three selected optimal features is outlined in Fig. 6. Nevertheless, the best cost value reached during the 250 iterations is right after the iteration 200. However, the cost function was not improved until it reached the maximum iteration.

On the other hand, the MSE values for the FFN algorithm, running on the three optimal features, is illustrated in Fig. 7. The FFN is converged just before the epoch 250, where it reached its minimum MSE value. However, this value remained stable until the epoch number 500. Which means that it is the best value that the FFN can obtain.

Subsequent to finding the optimal number and types of features using MOABC and training the FFN on them, several test cases are conducted in order to validate the developed model. This includes 100 new samples, taken randomly from 7 volunteers and other 7 new persons. The tests are conducted 50 times using different workstations, and the mean values are used to calculate the confusion matrix, considering the True Positive (TP) to be increased only as the required image appears as a first choice only, else, it will be considered a miss, and the True Negative (TN) will be increased.

After that, the Receiver Operating Characteristic (ROC) curve is built, which is illustrated in the Fig. 8. However, the tests show optimistic results with accuracy ratio around 93%, which means that the objectives of the proposed system are met, and the required image appears as the first choice for 92.8% of the searching times, which is an excellent contribution with clearly large enhancements over the current systems. In other meaning, the use of mindwave signals interpretation is a completely beneficial technique to retrieve the user's required information accurately and quickly as a first choice, especially in the era of IoT and big-data, which saves a lot of time and efforts for the users.

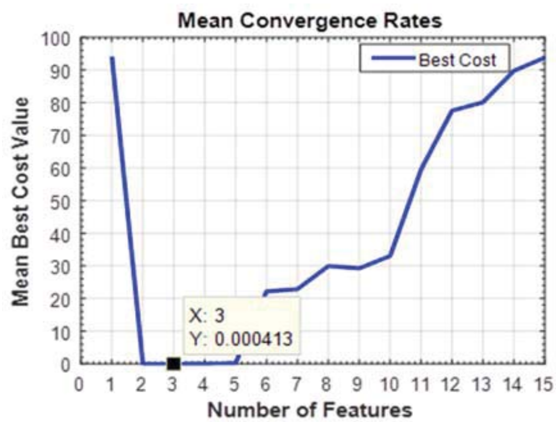

Fig. 5 MOABC mean convergence curve for different numbers of feature

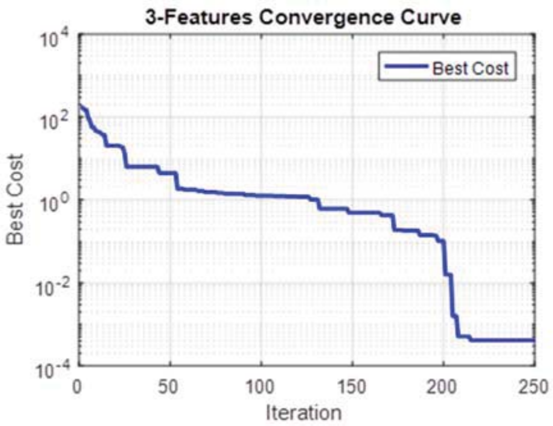

Fig. 6 MOABC mean convergence curve for the optimal features (Meditation, Alpha-high, and Theta)

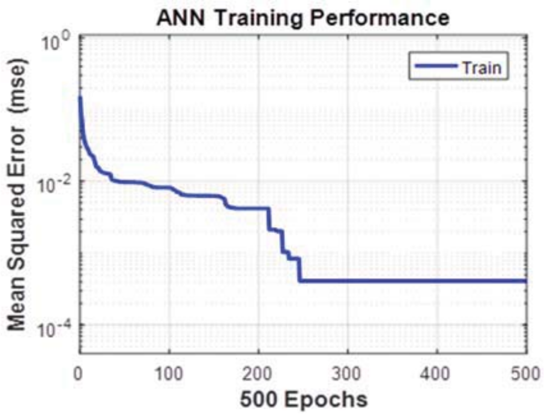

Fig. 7 FFN Training performance for the selected features (Meditation, Alpha, and Theta)

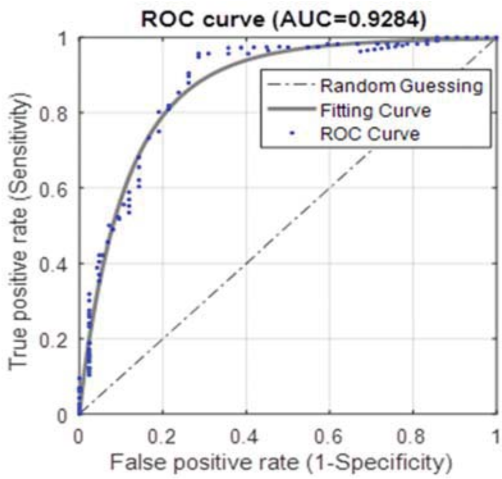

Fig. 8 ROC curve for the proposed system

V. Enhancements

This proposed approach is enhanced by adding other phases to the system, considering the features of IoT, big-data and distributed cloud environments. Hence, after collecting the mindwave meditation, theta and alpha-high signals associated only with the imagined information, and taking their corresponding output from the FFN engine. The outputs of a chain of consecutive thoughts are then interpreted using appropriate concepts utilized in NLP and Ontology fields. In order to construct an accurate set of mindwave triplets to turn them into a query understandable by the database engine. This query then is required to be processed accurately using an intelligent algorithm, such as FFN in order to be matched accurately with the optimal information stored in the database. Furthermore, database management algorithms such as MapReduce is required to be used along with the intelligent algorithm so as to identify the location of the information and then retrieve the most optimal answer related to the user's thought. This technique, which is still under development, at the time of writing this paper, provides an easy, fast and accurate content search technique that constantly provide the user with the required information as a first choice.

VI. Conclusion and Contributions

This work tried to find a solution to reduce the delays in search results and enhance its accuracy using the user's mindwave signals, to define the required search information exactly and directly as a first choice. Moreover, it proposed a novel method to extract the optimal number and types of features to be used in the classification process, as it is concluded from this work that the number and also the type of features affect the accuracy of the clustering algorithm.

A large number of various data were collected and various tests were conducted to validate the proposed system, which showed around 93% of accuracy. This finding contributes to the fields of big-data and the emerged fields of IoT, which contain a huge amount of data available on the private and public domains, and reflects positively in saving their users' times and efforts. Consequently, as a part of the VisualThoughts project, it provided an enhanced easy-to-use system to allow a better understanding of human thoughts; moreover, it represents them into an image.

This may constitute an introduction to complete NMP system and its applications in the fields of data contents search and queries, understanding brain vision, and rebuilding human memory. Some enhancements could be done on this proposed work, as it used 10 predefined words only, increasing the number of words is necessary to expand its domain. After that, this system can be integrated with techniques of NLP, Ontology and Symantec Web. Which will enhance the search and query for not only multimedia items, but also that goes further to the contents of these items in distributed systems on the cloud with big-data and IoT environments. Hence, this can be extended to provide a visual building for human active memory and thoughts in the shape of storytelling at a real time.

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