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RESEARCH ARTICLE

# ELECTRO-PHOTONIC IMAGING FOR DETECTING AN INTERVENTION (MEDITATION)

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**ABSTRACT**

Background: Electrophotonic Imaging (EPI) also known as Gas Discharge Visualization (GDV)is one of the instrument to capture the internal activities based on the stimulation of photon and electron emissions from the surface of the object.

Meditation is a family of complex emotional and attentional regulatory training mechanism and it involves uninterrupted monitoring to capture subtle internal processes. Several instruments are used to understand the impact of meditation by monitoring the brain waves online or by understanding the activities in the Default Mode Network. The objective of this study is to use the EPI data to establish a frame work for intervention recognition by training a neural network by capturing the subtler aspects of meditation.

**Methods:** A single group pre-post intervention study was carried out on 51 adults (32 males and 19 females) at Pyramid Valley International, Bengaluru, India. Anapanasati a focused attention meditation was given for 5 days. EPI data was captured before and after the intervention. The data was analyzed using IBM SPSS Neural network software.

**Results:** Meditation was found to have a significant impact on EPI parameters. Neural network was able to classify pre and post meditative population using EPI data with an accuracy ranging from 84% to 100%. The receiver operating characteristics (ROC) was captured for each of the classification and the area under the curve was close to unity.

**Conclusion:** Electrophonic Imaging combined with neural network works as a good framework for intervention recognition.



## INTRODUCTION

Electrophotonic Imaging (EPI) is based on the stimulation of photon and electron emissions from the surface of the object. The stimulation is provided by transmitting short electrical 10-microsecond pulses. The emitted particles accelerate in the electromagnetic field, generating electronic avalanches on the surface of the dielectric (glass) plate. The discharge causes glow from the excitement of molecules in the surrounding gas, and this glow is what is being measured by the EPI instrument. Voltage pulses stimulate optoelectronic emission, while intensifying this emission in the gas discharge, amplified by the electric field created. (Korotkov, 2011)

The resultant Electrophotonic Image represents a spatially distributed glow areas having varying brightness characteristics. Computer analysis of it reveals general, local and sector based details. (Alexandrova, Fedoseev, & Korotkov, 2004)

The parameters that Gas Discharge Visualization (GDV) provides are indicative of psycho-emotional and physiological states. It provides information about the stress and normal behavior of organs and organ system (Deshpande, Madappa, & Korotkov, 2013)

The coronal discharge around a human fingertip using an EPI instrument were used to study the effect of textiles on the human body (Ciesielska, 2007).

Psycho-emotional condition is defined by our feelings and thoughts. One of the main questions is what is contained in the EPI data physical or psychical component. The researchers showed that it is the mental state the quality of psychic energy of man. (Anufrieva, Anufriev, Starchenko, & Timofeev, n.d.).

EPI technique has been used to monitor the patients by comparing their normal Electrophotonic emissions before and after surgeries (Kostyuk, Cole, Meghanathan, Isokpehi, & Cohly, 2011).

EPI based analysis on degree of arterial hypertension concluded that EPI could be used to screen patients of hypertension with different levels of severity (Aleksandrova, 2009)

Sympathetic and Parasympathetic activities can be extracted from the EPI data. The quantitative difference between the two systems is given out as a parameter called the Activation Coefficient (AC) by the EPI software, it also gives Integral Entropy (IE) which is a measure of deviation from functional physiological state and psycho emotional balance.(Cohly, Kostyuk, Isokpehi, & Rajnarayanan, 2009)

Meditation is a unique state in which deep rest and increased internal attention exist simultaneously. Meditation is a state in which agroup of complex emotional and attentional regulatory training mechanisms coexist for the emotional balance and overall well-being(Lutz, Slagter, Dunne, & Davidson, 2008). There are two styles of meditation, one is, focused attention meditation, entails the voluntary focusing of attention on a chosen object. The other style, open monitoring meditation, involves nonreactive monitoring of the content of experience from moment to moment.(Lutz *et al*., 2008).

A cross sectional study on long term and short term anapanasati meditators showed health related improvements in EPI parameters.(Deo G, Kumar IR, Srinivasan TM, 2016)

One of the studies examined the dissociable neural effects of anapanasati focused-attention meditation on blood oxygen level dependent signals during cognitive performance with continuous performance test and emotion processing task(Lee *et al*., 2012).

The EPI technique may be a valuable clinical tool to assess rapid responses in patients to examine the effectiveness of energy medicine modalities and practices such as qigong. (Rubik & Brooks, 2005)

Among the various meditation practices, the most fundamental and widely studied form is concentrative or focused-attention meditation (FAM). FAM practitioners focus their entire attention upon an object or a bodily sensation and, whenever they are distracted by external stimuli or inner thoughts, they bring their attention back to that object or sensation. The goal is to achieve a clear (vivid) and unwavering (calm and stable) state free from distraction.(Lee *et al*., 2012)

The meditation effects are subtle and any online monitoring could have an effect on the overall outcome especially for anapanasati intervention. An offline technique like EPI could be appropriate.

The EPI data has a large number of parameters. They are multidimensional and non-linear, which calls for a pattern based approach. Artificial neural networks have been used in the literature for bio-medical applications.

An artificial neural network (ANN) consists of a series of interconnecting parallel nonlinear elements with limited number of inputs and outputs(Wd Hong *et al*., 2013).

Artificial Neural Network analysis is more successful than the conventional statistical techniques in predicting clinical outcomes when the relationship between variables that determine the prognosis is complex, multidimensional and non-linear (Wan-dong Hong, Ji, Wang, Chen, & Zhu, 2011)

The research on early prediction of diabetes using features of EPI Images also concluded that data can be used to train neural networks for classification of diseases for diagnosis.(Priya, 2013).

There have been very few studies in capturing subtle effects in an automated environment. This work uses the combination of EPI data and artificial neural network for recognizing the intervention (anapanasati meditation) and works as a frame work for intervention recognition.

## MATERIAL AND METHODS

***Design:*** This is a single group pre-post design carried out at the Pyramid Valley Meditation center in Bangalore. Consent to participate in the study was obtained in writing and authorized tools were used for data collection and analysis of results. This study was approved by the institutional ethical committee.

***Samples:*** This study was carried out by voluntary recruitment of 51 subjects consisting of 32 males and 19 females with a written consent attending a Karnataka Dhyana Mahachakra-1 at Pyramid valley International Bengaluru, India. The pre-intervention records were termed as non-Meditators and post intervention records as Meditators.

***Tool:*** An Electro Photonic Imaging (EPI) instrument is used to capture the data corresponding to 41 acupuncture points with a total of 82 parameters for both handsand an additional parameter corresponding to the overall energy called Activation coefficient. **Fig1** has the Electrophotonic Images of the first 3 fingers from the thumb. The image obtained from each of the fingers is divided into sectors as shown **Fig 1**. A number corresponding to the photo electronic emissions from each sector is computed and given in the form of a spread sheet by the EPI software.

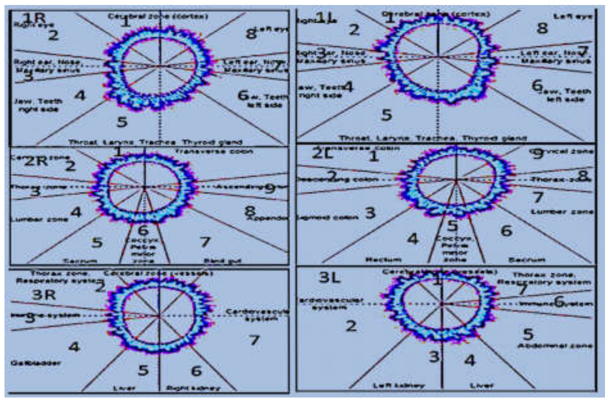


**Fig1 Electro Photonic Images of Fingers**

***Procedure:*** The data was captured from the 10 fingers for each subjects on the first day and on the last day of the meditation under identical measurement conditions. There are two ways to capture the EPI images with filter (physiological) and without filter (psycho-physiological). A thin plastic film is placed on the glass plate and the finger is placed on the film instead of putting it directly on the glass plate. The **Table1** below has the list of parameters for which the EPI instrument provided the coronary discharges as numbers.

***Data Processing*** EPI Images captured by the EPI instrument are loaded into the EPI software and the coronal discharges corresponding to the organs and organ systems is exported into a spread sheet. Each record is a pattern consisting of 82 parameters which are listed in **Table1**. There were two sets of 100 records (AKA patterns) captured with filter and without filter. The neural network is trained with 70% percent of the total patterns and the trained networks is used to classify the rest 30% of patterns as meditators or Non-meditators based on the neural network's learning.

**Table1** List of EPI parameters for which coronal Discharges were obtained from the EPI instrument

| Names of the Parameters | | |
|---|---|---|
| Right eye | Cerebralzone (cortex) | Cardiovascular system |
| Right ear, Nose, Maxillary sinus | Thorax zone | Cerebral zone(vessels) |
| Jaw, Teeth right side | Lumbar zone | Abdominal zone |
| Throat, Larynx, Trachea, Thyroid gland | Coccyx, Pelvis minor zone | Hypophysis-1 |
| Jaw, Teeth left side | Blind gut | Hypophysis-2 |
| Left ear, Nose, Maxillary sinus | Appendix | Thyroid gland-1 |
| Left eye | Ascending colon | Thyroid gland-2 |
| Urino-genital system | Transverse colon | Pancreas |
| Spleen | Descending colon | Adrenal |
| Nervous system | Thorax zone, Respiratory system | Jejunum |
| Epiphysis | Immune system 1 | Right part of heart |
| Duodenum | Immune system 2 | Liver |
| Ileum | Gallbladder | Mammary glands, Respiratory system |
| Activation coefficient | Integral area | Integral Entropy |

Several runs of the neural network were carried out on the two sets of 100 records with and without filter. The number of parameters in each record were selectively dropped from 83 to 1 interactively. In the initial stage all 82 parameters corresponding to ten fingers and activation coefficient were used. In the next step activation coefficient was removed from the list, and in the 3rd step, 41 parameters corresponding only to the right hand were used. The experiment was repeated with only the 41 parameters of the left hand and then for the individual parameters for the sectors in each finger.

## ANALYSIS AND RESULTS

The tables below show the results of classification of meditators and Non-Meditators by neural networks based on the input parameters and the architecture of the neural network.

The data in **Table 2** corresponds to the patterns captured without the filter from all the ten fingers from the right and left hand before and after the intervention. There are two types of patterns training and hold out. The Neural network was trained with 39 meditators (M) and 38 Non-meditators (NM), after the training it was given 23 patterns which had 10 M and 13NM. Neural network was able to classify 12 of the 13 NMs and 8 of the 10Ms correctly. The area under the ROC curve is 1 which means that the network was not over trained.

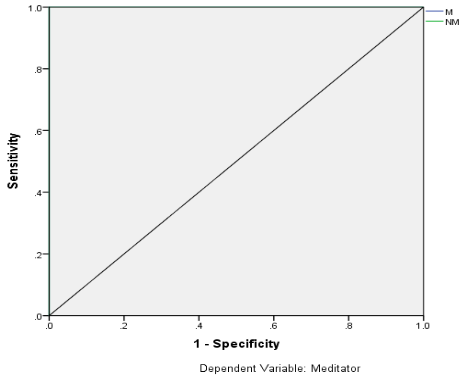
**Table 2** Classification using 83 Parameter without filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 39 | 0 | 100.0% |
| | NM | 0 | 38 | 100.0% |
| | Overall % | 50.6% | 49.4% | 100.0% |
| Holdout | M | 8 | 2 | 80.0% |
| | NM | 1 | 12 | 92.3% |
| | Overall % | 39.1% | 60.9% | 87.0% |

**M: Meditator, NM: Non-Meditator**

The data in **Table 3** shows that the neural network was trained with 73 patterns. A total of 27 patterns consisting of 12 M and 15 NM were used to test the classification accuracy of the neural network based on its learning. Neural network was able to identify all the 12 meditators correctly, (i.e. prediction accuracy was 100%) it has wrongly classified one of the NMs as M from a total population of 15 NMs.

**ROC Curve for Table2**




| Area Under the ROC curve | | |
|---|---|---|
| | | Area |
| Meditator | M | 1.000 |
| | NM | 1.000 |

**Table 3** classification with 83 Parameters with Filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 37 | 0 | 100.0% |
| | NM | 0 | 36 | 100.0% |
| | Overall Percent | 50.7% | 49.3% | 100.0% |
| Holdout | M | 12 | 0 | 100.0% |
| | NM | 1 | 14 | 93.3% |
| | Overall Percent | 48.1% | 51.9% | 96.3% |

**M: Meditator, NM: Non-Meditator**

The data in **Table 4** corresponds to the results of the experiment that we did in dropping 50 % of the parameters in a given pattern assuming that meditation would have significant impact on a majority of the meridians corresponding to both the right and left hand fingers. We have dropped all the data corresponding to the right hand fingers and have trained the neural network with the data from just the left hand fingers captured with Filter.

**Table 4** MLP with 41 parameters using left hand without filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 34 | 1 | 97.1% |
| | NM | 0 | 38 | 100.0% |
| | Overall Percent | 46.6% | 53.4% | 98.6% |
| Holdout | M | 8 | 6 | 57.1% |
| | NM | 8 | 5 | 38.5% |
| | Overall Percent | 59.3% | 40.7% | 48.1% |

**M:Meditator, NM: Non-Meditator**

The data in **Table 5** corresponds to the right hand fingers with filter. The classification accuracy is 100% for both meditators and Non-meditators. All the 11 Meditators and 14 Non-meditators were classified correctly by the neural network.

**Table5** 41 Parameters from Right hand with Filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 38 | 0 | 100.0% |
| | NM | 1 | 36 | 97.3% |
| | Overall Percent | 52.0% | 48.0% | 98.7% |
| Holdout | M | 11 | 0 | 100.0% |
| | NM | 0 | 14 | 100.0% |
| | Overall Percent | 44.0% | 56.0% | 100.0% |

**M: Meditator, NM: Non-Meditator**

The same experiment was repeated with the data taken from right hand fingers for the 41 parameters without the filter and the result in shown in **Table 6**.

**Table6,** 41 Parameters from the Right hand without filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 33 | 5 | 86.8% |
| | NM | 3 | 35 | 92.1% |
| | Overall Percent | 47.4% | 52.6% | 89.5% |
| Holdout | M | 6 | 6 | 50.0% |
| | NM | 5 | 7 | 58.3% |
| | Overall Percent | 45.8% | 54.2% | 54.2% |

**M: Meditator, NM: Non-Meditator**

The data in **Table 7** corresponds to data without filter for the left hand fingers. Neural network Classification accuracy for both left and right hand fingers taken without filter was low in comparison to that with the filter.

**Table -7** Classification with MLP with left hand 41 Parameters without filter

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 39 | 1 | 97.5% |
| | NM | 0 | 34 | 100.0% |
| | Overall Percent | 52.7% | 47.3% | 98.6% |
| Holdout | M | 5 | 5 | 50.0% |
| | NM | 11 | 5 | 31.2% |
| | Overall Percent | 61.5% | 38.5% | 38.5% |

**M: Meditator, NM: Non-Meditator**

The number of parameters in each pattern is further reduced to just three parameters corresponding to the Integral Area (IA), Integral Entropy (IE) and Activation Coefficient (AC). The result of the neural network classification for various combinations of the three parameters is shown below in **Table 8.**

**Table 8** Neural network Trained with 3 inputs from both Right and Left hand

| Neural Network Inputs | Filter | Classification Accuracy | Area under the ROC curve |
|---|---|---|---|
| AC,IA,IE Left side | Yes | 56.2% | .839 |
| AC,IA,IE Right side | Yes | 54.1% | .740 |
| AC,IA,IE, Left side | No | 42.9% | .718 |
| AC,IA,IE, Right side | No | 66.7% | .951 |

**Table9** Classification with 83 Parameters with Correct data

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 32 | 0 | 100.0% |
| | NM | 0 | 39 | 100.0% |
| | Overall Percent | 45.1% | 54.9% | 100.0% |
| Testing | M | 18 | 0 | 100.0% |
| | NM | 0 | 11 | 100.0% |
| | Overall Percent | 62.1% | 37.9% | 100.0% |

**M: Meditator, NM: Non-meditator**

**Table10** Classification with 83 Parameters with 50% of data Interchanged

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | M | NM | Percent Correct |
| Training | M | 20 | 10 | 66.7% |
| | NM | 8 | 24 | 75.0% |
| | Overall Percent | 45.2% | 54.8% | 71.0% |
| Testing | M | 11 | 9 | 55.0% |
| | NM | 8 | 10 | 55.6% |
| | Overall Percent | 50.0% | 50.0% | 55.3% |

**M: Meditator, NM: Non-Meditator**

The experiment was repeated with 50% incorrect data. That is 50% of the meditators were intentionally marked as Non-meditators and 50% of the Non-meditators were intentionally marked as meditators, accordingly the classification accuracy dropped to 50%. **Table9** below has the classification accuracy for the correct data and **Table10** shows the classification details of incorrect data.

## DISCUSSION

Neural network classification of pre and post data was consistent and accurate when trained with 83 parameters than with lower number of parameters. It is also observed that the training of the neural network with the right hand parameters showed good classification accuracy. The data captured with filter had more information related to meditation.

This study shows that the intervention of 5 days was effective enough to cause a definite change in the EPI parameters. The study on effect of anapanasati meditation showed statistically significant changes in the EPI parameters (Guru Deo, Itagi, Srinivasan, & Kushwah, 2015).

Future studies could be sector based analysis of EPI data for disease diagnosis or to understand the impact of the intervention on any particular meridian for EPI based disease diagnosis.

This study provides a framework for intervention recognition with EPI instrument and neural network. This framework couldbe used for therapeutic purposes to understand the impact of intervention on a disease

The study on autistic children(Kostyuk, Rajnarayanan, Isokpehi, & Cohly, 2010) used an EPI device and statistical analysis to bring out the statistical significance of EPI parameters in relation to the autistic disorder. Training the neural network with the statistically significant parameters will enable simultaneous diagnosis of multiple disorders with a single capture of EPI data.

## CONCLUSION

The EPI in combination with neural network was consistent and successful in classifying pre-post population using a 5 day meditation called Anapanasati as intervention.

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