ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 8, Issue 4, April 2019

Classification Of Fossilized Radiolarian Images Using Computational Intelligence Techniques

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Abstract— **Radiolarian assemblages have played a significant role as a biostratigraphic and paleoenvironmental tool used in the geological settings. These species can be used in studying sediments lacking calcareous fossils. Easy identification of these species would allow micropaleontologists to proceed further into studying the structure and way of living of these Radiolarians. The Efficient classifiers in light of using DCT transform with Principal component analysis (PCA) Neural Network. An alternate Cross-Validation dataset is used for authentic appraisal of the proposed gathering computation with respect to basic execution measures, for instance, MSE and request accuracy. The Average Classification Accuracy of PCA Neural Network containing one covered layers with 7 PE's dealt with in an ordinary topology is seen to be unrivaled (98.80%) for Training and cross-validation. Finally, perfect count has been delivered dependent on the best classifier execution.**

Index Terms— **Neural solution, MatLab, Matlab program, Microsoft excel.**

I. Introduction

The simplest definition is "the study of ancient life". Paleontology seeks information about several aspects of past organisms: "their identity and origin, their environment and evolution, and what they can tell us about the Earth's organic and inorganic past".

Paleontology or palaeontology is the scientific study of life that existed prior to, and sometimes including, the start of the Holocene Epoch (roughly 11,700 years before present). It includes the study of fossils to determine organisms' evolution and interactions with each other and their environments . Paleontological observations have been documented as far back as the 5th century BC. The science became established in the 18th century as a result of Georges Cuvier's work on comparative anatomy, and developed rapidly in the 19th century. This means that it aims to describe phenomena of the past and reconstruct their causes. Hence it has three main elements: description of the phenomena; developing a general theory about the causes of various types of change; and applying those theories to specific facts. When trying to explain past phenomena, paleontologists and other historical scientists often construct a set of hypotheses about the causes

For historical reasons paleontology is part of the geology departments of many universities, because in the 19th century and early 20th century geology departments found paleontological evidence important for estimating the ages of rocks while biology departments showed little interest. Paleontology also has some overlap with archaeology, which primarily works with objects made by humans and with human remains, while paleontologists are interested in the characteristics and evolution of humans as organisms. When dealing with evidence about humans, archaeologists and paleontologists may work together for example paleontologists might identify animal or plant fossils around an archaeological site,

Body fossils and trace fossils are the principal types of evidence about ancient life, and geochemical evidence has helped to decipher the evolution of life before there were organisms large enough to leave body fossils. Estimating the dates of these remains is essential but difficult: sometimes adjacent rock layers allow radiometric dating, which provides absolute dates that are accurate to within 0.5%, but more often paleontologists have to rely on relative dating by solving the "jigsaw puzzles" of biostratigraphy. Classifying ancient organisms is also difficult, as many do not fit well into the Linnaean taxonomy that is commonly used for classifying living organisms, and paleontologists more often use cladistics to draw up evolutionary "family trees". The final quarter of the 20th century saw the development of molecular phylogenetics, which investigates how closely organisms are related by measuring how similar the DNA is in their genomes. Molecular phylogenetics has also been used to estimate the dates when species diverged, but there is controversy about the reliability of the molecular clock on which such estimates depend.

However, classification or recognition of the microfossil that appear in these images is difficult task and needs human experience. But, if we consider the amount of the area that is covered by the paleontologist , it is more effective to provide automatic intelligent recognition or classification that simulates human experience. microfossil SEM images Classification System developed to simulate human experience by classifying microfossil images, This purposed work is organized as the follows: In this purposed work, microfossil SEM images Classification System which was developed to simulate human experience in the recognition of underwater shapes by using Pattern Averaging and Back Propagation Learning Algorithm, will be presented.

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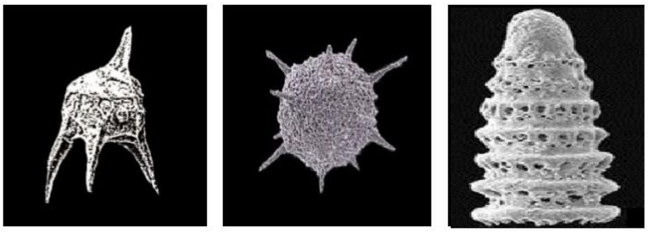
The reliability and the success of these systems are depend on the effectiveness of applied data pre-processing techniques and neural networks which can be used for efficient modeling of human's visual system during the recognition or classification of patterns. Neural networks have an important part in the modelling of human experience and decision making process into computers. some microfossil SEM images are shown in below figure 1



(a) (b) (c)

Figure 1:(a) Hozmadia reticulata (b) Triassospongosphaera multispinosa (c) Triassocampe aff. scalaris Dumitrica, Kozur & Mostler

II. RESEARCH METHODOLOGY

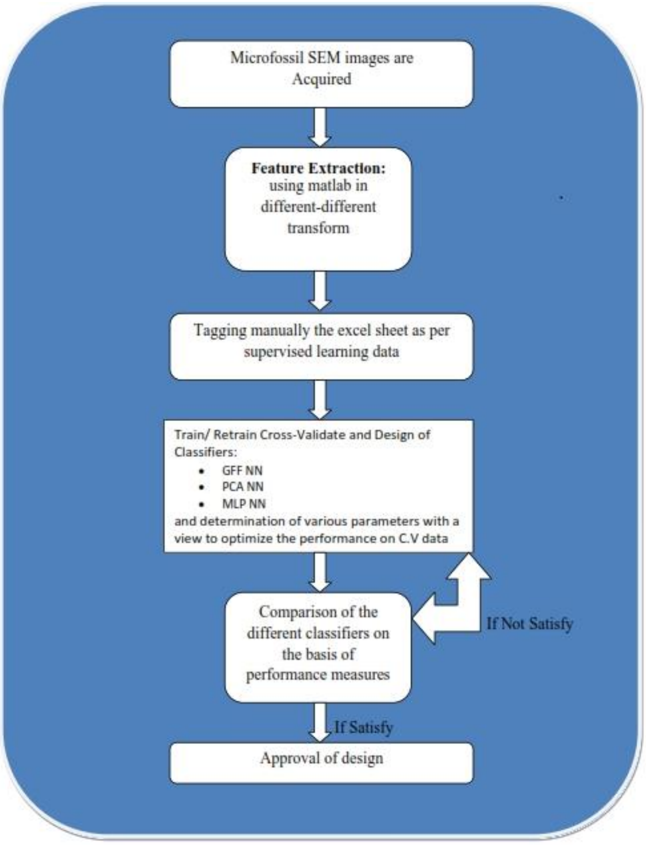


Figure.2 Methodology of work

It is order of Microfossil SEM images Using Neural Network Approaches.. Information obtaining for the proposed classifier intended for the characterization of Microfossil images. The most vital un associated includes and in addition coefficient from the images will be separated .In request to remove highlights DCT changed area will be utilized.

2.2Neural Networks

Following Neural Networks are tested:

Principal Component Analysis Neural network:

PCA is the optimal linear feature extractor. This means that there is no other linear system that is able to provide better features for reconstruction. One of the obvious PCA applications is therefore data compression. The goal here is to transmit as few features as possible while preserving as much of the source information as possible. This means that we have to squeeze into each feature as much information as possible from the source image. PCA chooses the projection that best reconstructs the data in the chosen subspace. A similar situation arises while addressing the classification problem. Hence, PCA is useful for classification. It has simple procedure and experience shows that it normally provides good features for classification.

Principal Component Analysis networks (PCAs) combine unsupervised and supervised learning in the same topology. PCA is an unsupervised linear procedure that finds a set of uncorrelated features, principal components, from the input.

The fundamental problem in pattern recognition is in defining the data features that are important for the classification (feature extraction). The goal is to transform the input samples into a new space (the feature space) such that the information about the samples is kept, but the dimensionality is reduced. This makes the classification job much easier, PCA is such a technique.

PCA can be used for data compression, producing the *M* most significant linear features. When used in conjunction with a multilayer Perceptron (MLP) to perform classification, the separability of the classes is not always guaranteed. If the classes are not sufficiently separated, the PCA will extract the largest projections while the separability could contain within some of the smaller projections.The importance of PCA analysis is that the number of inputs for the NN classifier can be significantly reduced. This results in a reduction of the number of required training patterns and a reduction in the training time of the classifiers.

2.3Learning Rules used:

➢ Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

➢ ***Conjugate Gradient***

CG is the most prevalent iterative technique for unraveling vast frameworks of direct conditions. CG is successful for frameworks of the shape A=xb-A (1) where x _is an obscure vector, b is a known vector, and A _is a known, square, symmetric, positive-unmistakable (or positive-uncertain) lattice. (Try not to stress in the event that you've overlooked what "positive-distinct" implies; we will survey it.) These frameworks emerge in numerous imperative settings, for example, limited contrast and limited component techniques for fathoming incomplete differential conditions, auxiliary examination, circuit investigation, and math homework.

Created by Widrow and Hoff, the delta govern, additionally called the Least Mean Square (LMS) strategy, is a standout amongst the most usually utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with lessen this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. On the off chance that the arrangement of information designs shape a directly autonomous set then subjective affiliations can be gotten the hang of utilizing the delta run the show.

It has been demonstrated that for systems with direct initiation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a paraboloid in n-space. Since the proportionality steady is negative, the chart of such a capacity is inward upward and has a base esteem. The vertex of this paraboloid speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector..

- ***Quick propagation***

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

- ***Delta by Delta***

Created by Widrow and Hoff, the delta manage, likewise called the Least Mean Square (LMS) technique, is a standout amongst the most regularly utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with diminish this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. In the event that the arrangement of info designs shape a directly free set then discretionary affiliations can be gotten the hang of utilizing the delta run the show.

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III. Result

The PCA neural system has been reproduced for 90 distinct images of microfossil Images out of which 63 were utilized for Training reason and 27 were utilized for cross validation. The simulation of the Best Neural network with maximum accuracy is shown below:

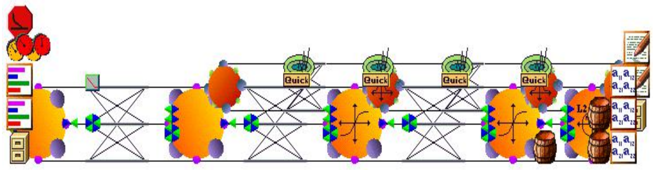

Figure4. The Best Neural network with maximum accuracy (PCA-QP)

Training Report of the Best Classifier:

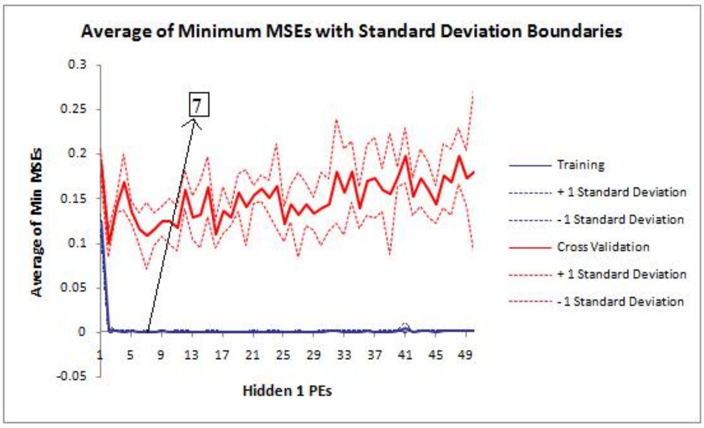

Table 1. Training and cross validation Report of the Best Classifier PCA-QP

Best Networks	Training	Cross Validation
Hidden 1 PEs	4	7
Run #	2	1
Epoch #	999	60
Minimum MSE	0.000205563	0.073041036
Final MSE	0.000205563	0.079122512

Test on Cross validation (CV):

Table 2. Confusion matrix table of Cross validation (CV)

Output / Desired	NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	NAME(HOZMAD IA RETICULATA)
NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	6	1	0
NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	0	13	0
NAME(HOZMAD IA RETICULATA)	0	0	7

Table 3: Performance Measures for cross validation

Performance	NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	NAME(HOZMAD IA RETICULATA)
MSE	0.05652042	0.033006313	0.014078795
NMSE	0.327011004	0.132206605	0.073310295
MAE	0.137171677	0.078281953	0.067183166
Min Abs Error	0.000995228	0.00040801	0.000131283
Max Abs Error	0.926501797	0.830302212	0.401069241
r	0.827426896	0.933214326	0.967906126
Percent Correct	100	92.85714286	100

Test on Training:

Table 6: Confusion matrix table of Training

Output / Desired	NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	NAME(HOZMAD IA RETICULATA)
NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	14	0	0
NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	0	32	0
NAME(HOZMAD IA RETICULATA)	0	0	17

Table 7: Performance Measures for training

Performance	NAME(TRIASSOS PONGOSPHAER A MULTISPINOSA)	NAME(TRIASSO CAMPE SCALARIS DUMITRICA)	NAME(HOZMAD IA RETICULATA)
MSE	0.000440952	0.000840633	0.000599569
NMSE	0.002551222	0.003363381	0.003043081
MAE	0.016802175	0.021010454	0.017636238
Min Abs Error	9.76997E-06	0.000304208	0.00017079
Max Abs Error	0.048377434	0.131164689	0.09668989
r	0.998865607	0.998327153	0.998699005
Percent Correct	100	100	100

IV. CONCLUSION

A From the results obtained in DCT domain it concludes that the PCA Neural Network with QP (Quick propagation) and hidden layer 1 with processing element 8 gives best results of 97.61% in Cross Validation while in training it gives 100% accuracy so overall accuracy is 98.80%.

ACKNOWLEDGMENT

We are very grateful to our HVPM College of Engineering and Technology to support and other faculty and associates of ENTC department who are directly & indirectly helped me for these paper.

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