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REVIEW ON A NEURAL NETWORK-BASED CLASSIFICATION OF WATER RESOURCE IMAGES

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Abstract: Image classification from a database is particularly difficult for traditional machine learning algorithms because of the high number of images and many details that describe an image. For these reasons, traditional machine are unstable to classify images from a database. These machines take long time for classification. Existing image storing systems such as QBIC and Visual SEEK limit classification mechanism to describe an image based on color information, or texture, or shape features. One of the existing methods for recognition, classification and retrieval of images is based on Neural Networks (NN). Neural Network is an information processing exemplar that is inspired by the way biological nervous systems, such as the brain, process information. Neural Network has ability to derive meaning from complicated or imprecise data. That can be used to extract patterns and detect trends. There hasn't been any significant work for water resource classification. Hence, a need for robust Neural Network with high classification accuracy is proposed in our project.

Keywords: Image classification, Neural Networks, GLCM

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INTRODUCTION

Water resources are under major stress around the world. Rivers, lakes, and underground water resources supply fresh water for irrigation, drinking, and sanitation, while the oceans provide habitat for a large share of the planet's food supply. Today, however, expansion of agriculture, diversion, over-use, and pollution threaten these irreplaceable resources in many parts of the globe.

Providing safe drinking water for the more than 1 billion people who currently lack it is one of the greatest public health challenges facing national

governments today. In many developing countries, safe water, free of pathogens and other contaminants, is unavailable to much of the population, and water contamination remains a concern even for developed countries with good water supplies and advanced treatment systems.

Surface water contamination from agricultural and urban runoff and wastewater discharges from industrial and municipal activities is of major concern to people worldwide. Classical models can be insufficient to visualize the result because the water resources variables used to describe dynamic pollution sources are complex, multivariable, and nonlinearly related. Artificial intelligence techniques with the ability to analyses multivariate water resources data by means of a sophisticated visualization capacity can offer an alternative to current models. Classified water resources are the need for future.

Clear goals relating to the quality of the relevant water resources must be established. A balance must be sought between the need to protect and sustain water resources on the one hand, and the need to develop and use them on the other. The quality objectives of the resource in question may relate to the Reserve, the in stream flow, the water level, the presence and concentration of particular substances in water, the characteristics and quality of the water resources and the in stream and riparian habitat, the characteristics and distribution of aquatic biota, the regulation or prohibition of in stream or land-based activities which may effects the quantity of water in or quality of the water resource and any other characteristics.

Countries of the Near East region have invested in water resources development during the past decades are generally better off in absorbing drought effects than those that adopted different policies. The utilization of water resources, intended initially for boosting agricultural production and providing drinking and industrial water supplies in addition to power generation, through the construction of water storage and transport infrastructure, buffered water shortages that resulted from drought episodes. The selection of river flow during wet periods regulated the availability of water resources and their partitioning over dry periods, allowing for the satisfaction of drinking water supplies, the maintenance of trees and at times even substantial crop production through supplementary or deficit-irrigation. While being non negligible, these achievements remain generally below the potential of adequate management of water resources for drought preparedness and moderation.

The inadequacy of conventional water management approaches to prepare for drought conditions stems from the fact that these approaches were established during and for periods of water abundance. The policy was to encourage water usage for higher crop production, so the measures taken were all oriented towards this policy, including the institutional setup, the norms and regulations, the technology and the practices. Now that water resources have become scarce and drought periods more frequent, the conventional water resources management approaches are no longer valid; they need to be reviewed and adapted to water-scarcity and drought conditions.

Freshwater accounts for only some 6 percent of the world's water supply, but is essential for human uses such as drinking, agriculture, manufacturing, and sanitation. As discussed above, two-thirds of global freshwater is found underground. If you dig deeply enough anywhere on Earth, you will hit water. Some people picture groundwater as an underground river or lake, but in reality it is rarely distinct water body (large caves in limestone aquifers are one exception). Rather, groundwater typically fills very small spaces (pores) within rocks and between sediment grains. It may lie hundreds of meters deep in deserts or near the surface in moist ecosystems. Water tables typically shift from season to season as precipitation and transpiration levels change, moving up during rainy periods or periods of little transpiration and sinking during dry phases when the rate of recharge (precipitation minus evaporation and transpiration that infiltrates from the surface) drops.

In temperate regions the water tends to follow surface topography, rising under hills where there is little discharge to streams and falling under valleys where the water table intersects the surface in the form of streams, lakes, and springs.

Image classification from a database is particularly difficult for traditional machine learning algorithms because of the high number of images and many details that describe an image. For these reasons, traditional machine are unstable to classify images from a database. Furthermore, these machines take long time for classification. Existing image storing systems such as QBIC [1] and Visual SEEK [2] limit classification mechanism to describe an image based on color information [3], texture, or shape features. One of the existing methods for recognition, classification and retrieval of images is based on Neural Networks (NN). If image is used as an input of NN, the number of input unit of NN are going to increasing and cause to The size of the NN also are increasing. Thus, because of existing many images that are classified and high number of input unit of NN, Learning of the NN is very difficult.

I. LITERATURE SURVEY

Classification of water resource images needs to be scrutinized by comprehensive cross validation to tune for accuracy and robustness in operational use. Other modes of acquisition as dual-poll and full colorimetric complex imagery (albeit with smaller footprint) may offer opportunities for polarimetry and complex analysis, which can greatly enhance the classification result [1].The comparisons to digitized ice charts naturally contain some errors due to this resolution difference, because all the details visible in the classification result are not present in the digitized ice chart. This also reduces the classification rates of the comparison made to the digitized ice charts [2]. Learning vector quantization (LVQ) tries to overcome the problem of model-based texture analysis in SAR images, which is crucial because of speckle and cartographic resampling, which makes both first-order statistics (space-varying Kappa distribution of intensity) and second-order statistics (space varying autocorrelation function) hard to estimate in a local window. But the limitation of the LVQ is after segmentation, grains, instead of pixels, are classified by means of an object-oriented classifier.

a preliminary study for mapping sea ice patterns (texture) with 100-m ERS-1 synthetic aperture radar (SAR) imagery is **gray-level co-occurrence matrices (GLCM)** to quantitatively evaluate textural parameters and representations and to determine which parameter values and representations are best for mapping sea ice texture. Findings define the quantization, displacement, and orientation values that are the best for SAR sea ice texture analysis using GLCM [2]. In GLCM, textural contexts of sea ice, rather than surface texture of sea ice types are used to classify the images. but limitation of GLCM is length of pattern is only 100-m.

Synthetic aperture radar (SAR) systems have by now become an essential tool for the scientific surveillance of ice-infested Arctic waters. Spaceborne SAR surveillance is comparably independent of daylight and cloud coverage conditions. While shipborne and airborne SAR cannot be used under adverse weather conditions or may simply be unavailable over remote Arctic regions, spaceborne SAR can acquire images over named regions on a regular and reliable basis. For about three decades, SAR satellites such as RADARSAT, ERS, or ENVISAT have been employed in scientific investigations and for navigational purposes. Among the particular areas of interest are ice drift [1]–[4], sea state and wave propagation into sea ice [5], [6], ice concentration, iceberg detection [7], and ice-type classification; see, e.g., [7]. The latter topic has attracted increased attention over the last years due to the impact of climate change on Arctic waters and global sea ice coverage and its practical implications for navigation and exploration in these latitudes.

SHORT HISTORY OF ANN'S: Artificial intelligence is not a new research field - ANNs have been in the attention of the scientists over the last 60 years. First studies on neural networks were done in 1943 by McCullough and Pitts. After a while, Rosenblatt conceived in 1959 the first learning algorithm, creating a model known as the perceptron, which was then only a solution to simple linear problems.

The first non-linear processing capabilities of ANNs were reported in 1974 by Werbos, and afterwards the interest of the scientific community steadily increased, boosted in the last years by the discovery of the back propagation algorithm and by the increase in computational power, due to the exponential advances in computer technology[5]. Artificial Neural Networks (ANNs) are non-linear mapping structures based on the function of the human brain. They are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values [3]. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. An ANN is a computational structure that is inspired by observed process in natural networks of biological neurons in the brain. It consists of simple computational units called neurons, which are highly interconnected. ANNs have become the focus of much attention, especially because of their wide range of applicability and the ease with which they can treat complicated problems. ANNs are parallel computational models comprised of densely interconnected adaptive processing units. These networks are fine-grained parallel implementations of nonlinear static or dynamic systems. A very important feature of these networks is their adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. ANNs are now being increasingly recognized in the area of classification and prediction, where regression model and other related statistical techniques have traditionally been employed [2].

There are several types of architecture of NNs. However, the two most widely used NNs Feed forward networks and recurrent networks. In a feed forward network, information flows in one direction along connecting pathways, from the input layer via the hidden layers to the final output layer. There is no feedback (loops) i.e., the output of any layer does not affect that same or preceding layer. Feed-forward neural networks, where the data ow from input to output units is strictly feed forward. The data processing can extend over multiple (layers of) units, but no feedback connections are present.

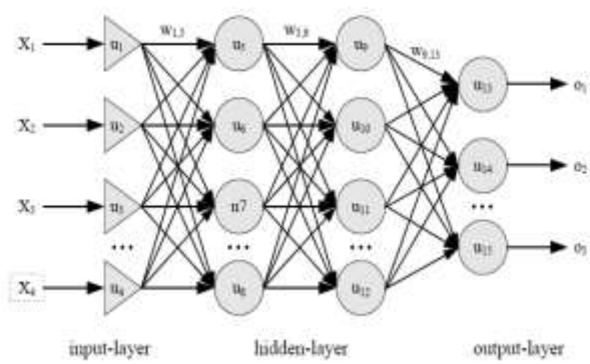

Fig 1: Neural network.

- **MLP Input Layer**

A vector of predictor variable values (x1…xp) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron [5].

- **MLP Hidden Layer**

Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (wji), and the resulting weighted values are added together producing a combined value uj. The weighted sum (uj) is fed into a transfer functions. The outputs from the hidden layer are distributed to the output layer.

- **MLP Output Layer**

The value from each hidden layer neuron is multiplied by a weight (wkj), and the resulting weighted values are added together producing a combined value u, at time of arriving at a neuron in the output layer j. The weighted sum (uj) is fed into a transfer function, s, which outputs a value yk. The y values are the outputs of the network. If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with categorical target variables, there are N neurons in the output layer producing N values, one for each of the N categories of the target variable.

IV .CONCLUSION

In this approach we have study work in the area of artificial neural network in water resource image classification. A very important feature of these networks is their adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available This study aimed to evaluate artificial neural network in the area of classification of water resource images on the basis of features of an image.

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