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# Lithofacies Classification from Well Log Data using Neural Networks, Interval Neutrosophic Sets and Quantification of Uncertainty

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***Abstract*****—** This paper proposes a novel approach to the question of lithofacies classification based on an assessment of the uncertainty in the classification results. The proposed approach has multiple neural networks (NN), and interval neutrosophic sets (INS) are used to classify the input well log data into outputs of multiple classes of lithofacies. A pair of $n$-class neural networks are used to predict $n$-degree of truth memberships and $n$-degree of false memberships. Indeterminacy memberships or uncertainties in the predictions are estimated using a multidimensional interpolation method. These three memberships form the INS used to support the confidence in results of multiclass classification. Based on the experimental data, our approach improves the classification performance as compared to an existing technique applied only to the truth membership. In addition, our approach has the capability to provide a measure of uncertainty in the problem of multiclass classification.

***Keywords*****—**Multiclass classification, feed-forward backpropagation neural network, interval neutrosophic sets, uncertainty.

## I. Introduction

With the ever increasing demands and escalating oil prices, exploration for fossil fuel is an ongoing activity running at a feverish pace. One of the key issues in reservoir evaluation using well log data is the prediction of petrophysical properties such as porosity and permeability. Of all petrophysical properties, permeability is one of the more important properties in reservoir engineering. Over the life of the reservoir, many crucial decisions depend on the ability to accurately estimate the formation permeability. Permeability is widely used to determine the well production rate of the hydrocarbon, such as oil or gas. There are many techniques available in petroleum engineering to better estimate the permeability. One of the successful methods is to pre-identify the flow units before estimating the permeability under each flow unit. Thus, the job of identifying lithofacies is a very crucial stage. This is to determine how to characterize the well into different flow units before estimating the permeability. Lithofacies such as sandstone, mudstone etc will affect the nature of the permeability, and thus directly related to the estimation of permeability. Beside the well log data, lithofacies are determined by expert geologist who has examined the actual rock samples known as “core data”. The expert geologist will normally put the core data into different classes. Although the core data is the most accurate way to separate the well into different flow unit, but core data are very expensive and difficult to obtain, Normally, the geologist will establish an interpretation model based on the available core and well log data, and use the established model to characterize those depths or wells around the region which are uncored. Thus, this is normally treated conventionally as a classification problem. However, due to the many environmental issues and measurement difficulties, this is normally a very complex task which has many uncertainties.

Normally, data collected from real world phenomena always contain imperfection. There are different aspects of imperfection defined by different researchers. Smets [1] considered imperfection in three aspects: imprecision, inconsistency, and uncertainty. He suggested that imprecision occurs if several worlds are compatible with the available information whereas inconsistency happens when there is no world agreeable to the information. Examples of imprecision are vagueness, ambiguity, incompletion, error, and inaccuracy whereas examples of inconsistency are confliction, incoherence, and confusion. Uncertainty occurs when there is a lack of information about the world for deciding if the statement is true or false. These three aspects are related to one another. For instance, imprecision in the data is a major cause of uncertainty [1].

In geographic environment, Duckham [2] suggested that uncertainty arises because geographic information is always imperfect. He proposed three types of imperfection, which are imprecision, inaccuracy and vagueness. Imprecision occurs when data is incomplete or lack of detail. Inaccuracy happens when errors exist in the observation. Vagueness deals with the concept of boundaries which cannot be defined precisely.

Fisher [3] separated uncertainty into three types: error, vagueness, and ambiguity. Error can result from several sources such as measurement, data entry, or processing. It can also occur from the lack of knowledge about data or lack of ability in measurement. Vagueness refers to the indeterminate boundary. Ambiguity occurs when the decision deals with doubt.

Imperfection can be categorized into various taxonomies according to different views of researchers. From these taxonomies, the causes of uncertainty are revealed in various aspects. In this paper, we deal with lithofacies classification from well log data collected from real and practical data in the oil and gas industry. Hence, the data set always contain imperfection. In the past, there are several techniques applied to reservoir evaluation from well log data [4], [5], [6], [7].

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However, there are little researches focus on uncertainty for reservoir evaluation. In this experiment, two causes of uncertainty are explored. Error and vagueness are quantified in order to enhance the classification of well log data into multiple classes of lithofacies. We apply multiclass neural networks [8] and interval neutrosophic sets [9] for the classification.

In general, there are two approaches used for multiclass neural network classification. First, multiple binary neural networks are trained, and outputs obtained from these networks are classified into multiple classes. The flexibility of this approach is that individual network can be modeled with different architectures which is suitable for different classes. However, each neural network is trained based on local knowledge which may produce overlaps or gaps in the classification boundary zone [8]. The second approach is the use of a single neural network with multiple outputs. The network architecture used for this approach is usually more complex than those used in the first approach, but the classification boundaries are sharp [8]. We apply the second approach in is paper.

There are various techniques used to generate codewords for a single neural network with multiple outputs [10], [11], [12]. The codeword designed for each class is a binary string of length $n$. One of the models using a simple codeword is One-Against-All neural networks (OAA). In this technique, the length of the codeword is equal to the number of classes. The $k$-th bit in the codeword of the $k$-th class is equal to 1, and the rest is equal to 0. In the testing phase, a sample is assigned to the $k$-th class if the $k$-th bit in the predicted binary string has the highest confidence value. We apply OAA technique in this experiment.

Extending the work from our previous papers [13], [14], we have applied interval neutrosophic sets to represent uncertainty in the binary classification and they are also applied in this paper. The membership of an element to the interval neutrosophic set is expressed by three values: truth membership, indeterminacy membership, and false membership. The three memberships can be any real sub-unitary subsets and can represent imprecise, incomplete, inconsistent, and uncertain information [15]. For example, let $A$ be an interval neutrosophic set, then $x(80, \{25, 35\}, 15)$ belongs to $A$ means that $x$ is in $A$ to a degree of $80\%$, $x$ is uncertain to a degree of $25\%$ or $35\%$, and $x$ is not in $A$ to a degree of $15\%$. This paper follows the definition of interval neutrosophic sets that is defined in [9]. Let $X$ be a space of points (objects). An interval neutrosophic set in $X$ is defined as:

$$\begin{array}{c} A = \{x(T_A(x), I_A(x), F_A(x))|x \in X \wedge \\ T_A : X \longrightarrow [0,1] \wedge \\ I_A : X \longrightarrow [0,1] \wedge \\ F_A : X \longrightarrow [0,1]\} \end{array} \quad (1)$$

where

$T_A$ is the truth membership function,
$I_A$ is the indeterminacy membership function,
$F_A$ is the false membership function.

In this experiment, two multiclass neural networks with multiple outputs are trained with the same input feature vectors but disagree in the target outputs. The first network predicts the degrees of truth membership and the second network predicts the degrees of false membership. The false membership is assumed to be the complement of the truth membership. However, both predicted memberships may not be one hundred percent complement to each other. Vagueness may occur in the boundary between these two memberships. Furthermore, errors in the prediction are also quantified in this experiment. A multidimensional interpolation method is used to estimate these errors. This paper represents error in the form of indeterminacy membership. Together the truth, indeterminacy, and false memberships form an interval neutrosophic set. The three memberships are used to classify well log data into multiple lithofacies. In addition, vagueness and error are combined to support the confidence in the classification as well.

The rest of this paper is organized as follows. Section II explains the proposed method for multiclass classification using neural networks, interval neutrosophic sets, and a multidimensional interpolation. Section III describes the data set and results of our experiment. Conclusions and future work are presented in Section IV.

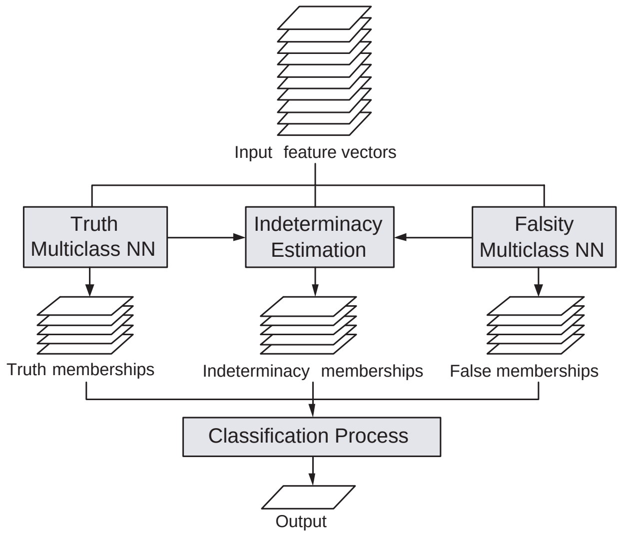


Fig. 1 The proposed multiclass neural network model based on interval neutrosophic sets

## II. Assessment of Uncertainty using Multiclass Neural Networks and Interval Neutrosophic Sets

In this paper, interval neutrosophic sets and neural networks with multiple outputs are used for multiclass classification. In addition, a multidimensional interpolation technique is used to quantify errors in the classification as well. Fig.1 shows our proposed model. Truth Multiclass NN and Falsity Multiclass NN are feed-forward backpropagation neural networks with multiple outputs. Both networks have the same architectures and properties. The only difference is that the truth network is trained to predict degrees of truth membership, but falsity network is trained to predict degrees of false membership using the complement of target codewords used in the truth network. Both networks apply one-against-all technique in which the length of the codeword is equal to the number of classes. If the codeword used to train the truth network for the $k$-th class has a bit at the position $k$-th equal to 1, and the rest is equal to 0 then the codeword used to train the falsity network for the $k$-th class at the $k$-th bit is equal to 0 and the rest is equal to 1.

In the testing phase, our proposed networks predict $n$-pairs of truth and false membership values for each input pattern of $n$-class data set. Errors occurred in the prediction of each pair of truth and false memberships are also estimated and represented as indeterminacy memberships. In order to estimate errors in the prediction of truth memberships, errors obtained from the truth network during training are plotted in the multidimensional feature space of the training input patterns. After that, a multidimensional interpolation technique is applied to estimate errors of the unknown input patterns. Estimated errors in the prediction of false memberships are also calculated in the same way as the estimated errors for the truth memberships.

Therefore, the result obtained from each pair of truth and false memberships contains a triplet $(t, \{e^t, e^f\}, f)$ where $t$ is the truth membership, $\{e^t, e^f\}$ is the indeterminacy membership containing estimated errors for truth and false memberships, and $f$ is the false membership. Furthermore, vagueness occurred in the boundary between truth and false memberships is also quantified in order to support confidence in the classification. In this paper, vagueness is calculated as the difference between truth and false membership values. If the difference between these two values is high then the degree of vagueness is low. If the difference is low then the degree of vagueness is high. Hence, vagueness for each output can be computed as $1 - |t - f|$.

Let $A_j$ be an interval neutrosophic set of the $j$-th output. $A_j$ can be defined as $A_j = \{x(T_{A_j}(x), I_{A_j}(x), F_{A_j}(x))\}$ where $T_{A_j}$ is the truth membership function of the $j$-th output, $I_{A_j}$ is the indeterminacy membership function of the $j$-th output, and $F_{A_j}$ is the false membership function of the $j$-th output. Let $e_j^t(x_i)$ be an estimated error in the prediction of the truth membership at cell $x_i$ of the $j$-th output. Let $e_j^f(x_i)$ be an estimated error in the prediction of the false membership at cell $x_i$ of the $j$-th output. Both estimated errors constitute the indeterminacy membership.

The weights for the truth and false memberships are calculated as the complement of errors estimated for the truth and false membership, respectively. These weights are considered as the degrees of certainty in the prediction. In this paper, the certainty in the prediction of the false membership is considered to be equal to the certainty in the prediction of the non-false membership, which is the complement of the false membership value. Let $w_j^t(x_i)$ and $w_j^f(x_i)$ be the weights of the truth and false membership values at cell $x_i$ of the $j$-th output. The result $O_j(x_i)$ of the dynamic combination among the truth, indeterminacy, and false memberships at cell $x_i$ of the $j$-th output can be calculated using equations below.

$$O_j(x_i) = (w_j^t(x_i) \times T_{A_j}(x_i)) + (w_j^f(x_i) \times (1 - F_{A_j}(x_i))) \quad (2)$$

$$w_j^t(x_i) = \frac{1 - e_j^t(x_i)}{(1 - e_j^t(x_i)) + (1 - e_j^f(x_i))} \quad (3)$$

$$w_j^f(x_i) = \frac{1 - e_j^f(x_i)}{(1 - e_j^t(x_i)) + (1 - e_j^f(x_i))} \quad (4)$$

For each input pattern of $n$-class data set, each result $O_j(x_i), j = 1, 2, ..., n$ obtained from the dynamic combination at cell $x_i$ is used to create each bit in a binary string. If the $k$-th output has the highest result then the $k$-th bit in the binary string is set to a value 1, and the rest is set to a value 0. The input pattern is assigned to the $k$-th class if the binary string has the $k$-th bit equal to 1. In this paper, the average of all errors and vagueness obtained from the prediction of all multiple outputs for each input pattern at cell $x_i$ is used to support the confidence in the multiclass classification as well.

## III. Experiments

### A. Data Set

The data set used in this study is taken from a real reservoir. There are four wells available in this reservoir. The actual well locations lie approximately on a straight line with the following order: Well 3, Well 1, Well 2 and Well 4. The well logs used in this experiment are gamma ray (GR), deep resistivity (RDEV), shallow resistivity (RMEV), flushed zone resistivity (RXO), bulk density (RHOB), neutron porosity (NPHI), photoelectric factor (PEF), and sonic travel time (DT). These constitute the eight inputs to the neural networks. There are eleven lithofacies available in this reservoir and they form the outputs. The log data are recorded from different wells at various depths. All variables are normalized within the range of $[0, 1]$. In order to classify well log data into the eleven output classes, data obtained from all four wells are used in this experiment. For blind testing purpose and testing the applicability of our approach in “cross-well” prediction, we use 269 data obtained from wells 1, 3, and 4 for training and 105 data from well 2 are used for testing.

### B. Experimental Methodology and Results

In this experiment, two feed-forward backpropagation neural networks with multiple outputs are trained using one-against-all technique in order to predict degrees of truth memberships and degrees of false memberships. Both networks contain eight input nodes, eleven output nodes, and one hidden layer constituting of sixteen neurons. The same parameter values are applied to the two networks and both networks are initialized with the same random weights. The only difference is that the target codewords for the falsity network are equal to the complement of the target codewords used to train the truth network.

After eleven pairs of truth and false membership values are predicted for each unknown well log input pattern, vagueness and errors are estimated for each pair. Vagueness can be computed using the difference between truth and false membership values: $1 - |t - f|$. In order to estimate errors in the prediction of truth membership, errors obtained from training the truth network are plotted in the well log input

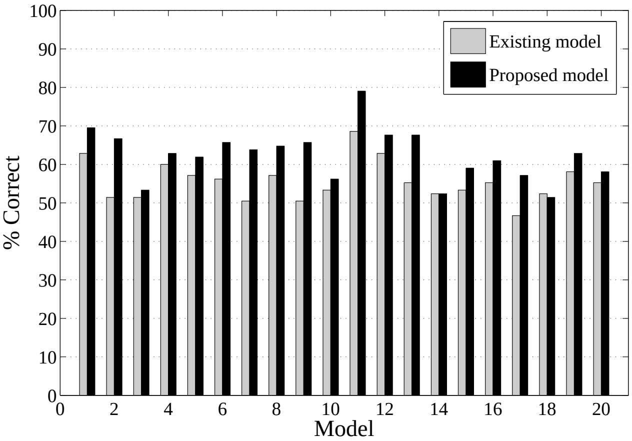


Fig. 2 Classification accuracy for the test data set obtained by applying the existing model using only the truth memberships and the proposed model using the three memberships

feature space. After that, a multidimensional interpolation is used to estimate error for the unknown or test input pattern. Error estimation in the prediction of false memberships is also calculated using the same technique as the error estimation for the truth memberships.

After errors for truth and false memberships are estimated, indeterminacy memberships are formed. The three memberships for each output are then combined using equation 2. The result obtained from the combination for each output is used to create each bit in a binary string. The bit in a binary string is set to a value 1 if the output correspond to this bit has the highest result while the remaining bits are set to 0. The well log input pattern is assigned to the $k$-th class if the binary string has the $k$-th bit equal to 1. In order to support the confidence in the classification, uncertainty in the classification for each input pattern is determined. In this experiment, we found that applying both causes of uncertainty gives a better uncertainty indication than using only one cause of uncertainty. Consequently, we apply the average of vagueness and errors obtained from eleven pairs of outputs to determine the level of uncertainty in multiclass classification for each input pattern.

Twenty pairs of feed-forward backpropagation neural networks with multiple outputs are trained with twenty different randomized training sets. Fig. 2 shows classification accuracy for the test data set obtained from twenty pairs of networks. In this paper, we do not consider the optimization of the prediction. Instead our purpose is to test a new approach that provides an estimate of the uncertainty of the classification. The results obtained from our proposed model are compared to the results obtained from the existing one-against-all (OAA) neural network model that applies to only the truth memberships for the multiclass classification. This figure shows that eighteen results produced from our technique outperform the results produced from the existing technique. The maximum of the total correct cell obtained from our approach is 79.05 whereas the maximum of the total correct cell obtained from the existing technique is 68.57. Moreover, the average of the total correct cell obtained from our technique is 62.33 whereas the average of the total correct cell obtained from the existing technique is 55.52.

TABLE I

SAMPLE OUTPUTS FROM THE TRADITIONAL CLASSIFICATIONS BASED ON TRUTH MEMBERSHIP VALUES (T) COMPARING TO THE OUTPUTS AND THEIR UNCERTAINTIES FROM OUR PROPOSED MODEL (TIF) FOR THE TEST SET OF WELL LOG DATA

| Actual class | Predicted class (T) | Predicted class (TIF) | Uncertainty value (TIF) | Uncertainty level (TIF) |
|---|---|---|---|---|
| 5 | 2 | 2 | 0.1809 | High |
| 2 | 10 | 8 | 0.1518 | High |
| 8 | 8 | 3 | 0.1344 | High |
| 4 | 8 | 2 | 0.1259 | High |
| 5 | 4 | 5 | 0.1139 | Med |
| 4 | 2 | 4 | 0.0808 | Med |
| 1 | 10 | 1 | 0.0749 | Med |
| 2 | 3 | 2 | 0.0626 | Low |
| 6 | 6 | 6 | 0.0299 | Low |
| 2 | 2 | 2 | 0.0156 | Low |

Furthermore, our approach has an ability to represent uncertainty in multiclass classification. The results obtained from model 11 (Fig. 2) are shown in Table I. This table shows 10 out of 105 samples of individual predicted output resulted from the traditional approach comparing to individual predicted output and their uncertainties resulted from our proposed model for the test set of well log data. Uncertainty attached to each predicted output can be used to support the confidence in the multiclass classification. The highest uncertainty value obtained from this experiment is 0.1809, the lowest uncertainty value is 0.0156, and the average of these uncertainties is 0.0874. We categorized uncertainty values obtained from this experiment into nine groups. These groups are separated into three levels: High, Med, and Low. Table II shows levels of uncertainty together with the total number of correct and incorrect outputs. We found that eight of the top ten samples that have high uncertainty values are incorrectly classified. This result shows that uncertainty value computed from vagueness and error can be used to enhance the decision making for the multiclass classification. For example, the actual class of the output in the first row of table I is 5, but the predicted outputs obtained from our proposed model and the traditional model are classified as 2, which are wrong. The traditional model cannot explain anything about uncertainty occurred in the classification. However, our proposed model can represent uncertainty in this classification with a value 0.1809, which is High. Hence, the decision makers can classify the unknown patterns by using uncertainty value to support their confidence in the classification.

From the results obtained from model 11, we also found that all incorrect outputs are in the transition zone between two classes. From the previous paragraph, we also know that most outputs that have high uncertainty level are misclassified. Hence, misclassified outputs with high uncertainty level are in the transition zone. The decision makers can apply these knowledge to improve the lithofacies classification. First, all predicted outputs are ordered by depth. Second, each output

TABLE II

TOTAL NUMBER OF CORRECT AND INCORRECT OUTPUTS PREDICTED FROM THE PROPOSED MODEL FOR THE TEST SET OF WELL LOG DATA

| Uncertainty value | Total number of correct cell | Total number of incorrect cell | Uncertainty level |
|---|---|---|---|
| 0.1625 - 0.1809 | 0 | 1 | High |
| 0.1442 - 0.1624 | 1 | 1 | High |
| 0.1258 - 0.1441 | 1 | 6 | High |
| 0.1074 - 0.1257 | 15 | 5 | Med |
| 0.0890 - 0.1073 | 15 | 3 | Med |
| 0.0707 - 0.0889 | 21 | 4 | Med |
| 0.0523 - 0.0706 | 16 | 2 | Low |
| 0.0339 - 0.0522 | 8 | 0 | Low |
| 0.0156 - 0.0338 | 6 | 0 | Low |

TABLE III

SAMPLES OF UPDATED OUTPUTS FROM OUR PROPOSED MODEL FOR THE TEST SET OF WELL LOG DATA

| Depth | Actual class | Predicted class | Uncertainty value | Uncertainty level | predicted class (update) |
|---|---|---|---|---|---|
| 0.6359 | 4 | 4 ✓ | 0.0970 | Low | 4 ✓ |
| 0.6388 | 2 | 4 × | 0.1089 | Med | 4 × |
| 0.6403 | 4 | 4 ✓ | 0.0808 | Low | 4 ✓ |
| 0.6519 | 4 | 2 × | 0.1260 | High | 4 ✓ |
| 0.6533 | 10 | 8 × | 0.1368 | High | 8 × |
| 0.6577 | 8 | 8 ✓ | 0.0585 | Low | 8 ✓ |
| 0.6606 | 4 | 8 × | 0.1335 | High | 8 × |
| 0.6621 | 2 | 8 × | 0.1518 | High | 2 ✓ |
| 0.6664 | 1 | 2 × | 0.1086 | Med | 2 × |
| 0.6737 | 2 | 2 ✓ | 0.0626 | Low | 2 ✓ |
| 0.7260 | 2 | 2 ✓ | 0.0718 | Low | 2 ✓ |
| 0.7304 | 2 | 2 ✓ | 0.0863 | Low | 2 ✓ |

that has high uncertainty level is revisited. For each output with high uncertainty level, uncertainties belonging to its neighbour outputs are compared. The neighbour with a lower uncertainty value is considered. Final, the output is reclassified to the same category as the one belonging to the neighbour that has a lowest uncertainty value. Table III shows 12 out of 105 samples of individual predicted output ordered by depth. For example, the output in the fourth row of this table was classified into class 2, and its uncertainty level is high. Hence, this output have to be revisited again. The uncertainty values of its neighbours are compared. We found that the upper neighbour has a lower uncertainty value. Therefore, this output is reclassified from class 2 into class 4. From this experiment, we found that the maximum of the total correct cell obtained from our approach is increased from 79.05 to 80.

## IV. CONCLUSION AND FUTURE WORKS

This paper represents a novel approach for lithofacies classification from well log data. Interval neutrosophic sets and multiclass neural networks are integrated in order to express uncertainty in the classification. The truth and false memberships are predicted using two one-against-all neural networks whereas the indeterminacy memberships are estimated from errors occurred in the predictions using a multidimensional interpolation method. In addition, vagueness occurred in the classification is also computed. We found that assessment of two causes of uncertainty which are error and vagueness can be used to support confidence in multiclass classification. The experimental results indicate that our proposed model improves the classification performance compared to a traditional approach applying only single one-against-all neural network applied only to the truth membership values. In the future, we will extend our model to incorporate ensemble neural networks.

## REFERENCES

[1] P. Smets, *Uncertainty Management in Information Systems: From Needs to Solutions*. Kluwer Academic Publishers, 1997, ch. Imperfect information: Imprecision-Uncertainty, pp. 225–254.
[2] M. Duckham, “Uncertainty and geographic information: Computational and critical convergence,” in *Representation in a Digital Geography*. New York: John Wiley, 2002.
[3] P. F. Fisher, *Geographical Information Systems: Principles, Techniques, Management and Applications*, 2nd ed. Chichester: John Wiley, 2005, vol. 1, ch. Models of uncertainty in spatial data, pp. 69–83.
[4] C. C. Fung, K. W. Wong, and H. Eren, “Modular Artificial Neural Network for Prediction of Petrophysical Properties From Well Log Data,” in *IEEE Transactions on Instrumentation and Measurement*, vol. 46, no. 6, 1997, pp. 1259–1263.
[5] H. Crocker, C. C. Fung, and K. W. Wong, “The STAG Oilfield Formation Evaluation: A Neural Network Approach,” *Australian Petroleum Production and Exploration Association APPEA99 Journal*, vol. 39, part1, pp. 451–460, 1999.
[6] K. W. Wong and T. D. Gedeon, “Fuzzy Rule Interpolation for Multidimensional Input Space with Petroleum Engineering Application,” in *Proceedings of Joint 9th IFSA World Congress and 20th NAFIPS International Conference*, Vancouver, Canada, July 2001, pp. 2470–2475.
[7] K. W. Wong, Y. S. Ong, T. D. Gedeon, and C. C. Fung, “Reservoir Characterization Using Support Vector Machines,” in *Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation*, vol. 2, November 2005, pp. 354–359.
[8] G. Ou, Y. L. Murphey, and L. A. Feldkamp, “Multiclass Pattern Classification Using Neural Networks,” in *Proceeding of the 17th International Conference on Pattern Recognition (ICPR)*, 2004, pp. 585–588.
[9] H. Wang, D. Madiraju, Y.-Q. Zhang, and R. Sunderraman, “Interval neutrosophic sets,” *International Journal of Applied Mathematics and Statistics*, vol. 3, pp. 1–18, March 2005.
[10] R. Erenshteyn, P. Laskov, D. M. Saxe, and R. A. Foulds, “Distributed Output Encoding for Multi-Class Pattern Recognition,” in *Proceeding of the 10th International Conference on Image Analysis and Processing (ICIAP)*, 1999, pp. 229–234.
[11] T. G. Dietterich and G. Bakiri, “Solving Multiclass Learning Problems via Error-Correcting Output Codes,” *Journal of Artificial Intelligence Research*, vol. 2, pp. 263–286, 1995.
[12] K. Crammer and Y. Singer, “On the Learnability and Design of Output Codes for Multiclass Problems,” *Machine Learning*, vol. 47, no. 2-3, pp. 201–233, 2002.
[13] P. Kraipeerapun, C. C. Fung, and W. Brown, “Assessment of Uncertainty in Mineral Prospectivity Prediction Using Interval Neutrosophic Set,” in *Proceedings of the International Conference on Computational Intelligence and Security*, ser. Lecture Notes in Artificial Intelligence, no. 3802. Xi’an, China: Springer Verlag, 2005, pp. 1074–1079.
[14] P. Kraipeerapun, C. C. Fung, W. Brown, and K. W. Wong, “Mineral Prospectivity Prediction using Interval Neutrosophic Sets,” in *IASTED International Conference on Artificial Intelligence and Applications*, Innsbruck, Austria, February 2006, pp. 235–239.
[15] H. Wang, F. Smarandache, Y.-Q. Zhang, and R. Sunderraman, *Interval Neutrosophic Sets and Logic: Theory and Applications in Computing*, ser. Neutrosophic Book Series, No.5. http://arxiv.org/abs/cs/0505014, May 2005.