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Deep Learning and Fuzzy Rule-Based Hybrid Fusion Model for Data Classification

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***Abstract:** Data mining is the promising field that attracted the industries to manage huge volumes of data. The most effective and challenging techniques of data mining is data classification. The main intension of this research is to design and develop a data classification strategy based on hybrid fusion model using the deep learning approach, Adaptive Lion Fuzzy System (ALFS), and Robust Grey wolf based Sine Cosine Algorithm based Fuzzy System (RGSCA-FS). The hybrid model consists of three phases: In the first phase, the data is classified using ALFS and the rule base of the fuzzy system is updated by optimally generating the rules using adaptive lion optimization (ALA) from the training data. The second step is the fuzzification process, which converts the scalar values in the training data into fuzzy values with the help of membership function, which is based on Adaptive Genetic Fuzzy System (AGFS). Finally, the classified score of data instances is determined using defuzzification process, which converts the linguistic variable into fuzzy score. In the second phase, the data is classified using Robust Grey wolf based Sine Cosine Algorithm based Fuzzy System (RGSCA-FS), which is used for selecting the optimal fuzzy rules. In the third phase, the data is classified using deep learning networks. The outputs from three phases are fused together using the hybrid fusion model for which the weighed fusion is employed. The performance of the system is validated using three different datasets that are available in UCI machine learning repository. The proposed hybrid model outperforms the existing methods with sensitivity of 0.99, specificity of 0.9350, and accuracy of 0.9411, respectively.*

***Keywords:** data classification, data mining, defuzzification, fuzzy rules, membership function.*

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I. INTRODUCTION

One of the promising fields for handling large volume of data is data mining. Newly arrived data is complex and dynamic in nature. Hence, the data are not analyzed according to the requirement of the user. The effective and challenging approach in data mining is data classification.

The classification algorithms, such as decision tree classifiers [5], Bayesian classifiers [6], rule-based classifiers [7], Artificial Neural Networks (ANNs) [8], Lazy Learners, ensemble methods [9], and Support Vector Machines (SVMs) [10] are used for classifying the data in data mining. The challenges in the large-scale data necessitate deep learning and are handled by the traditional classification techniques. For the unstructured data, these conventional techniques do not provide classification accuracy. Various techniques are developed to mine the classification rule from the numeric data. Feasible solutions for the imbalanced datasets are provided using Systems based on fuzzy logic [11]. The fuzzy logic system [12] is categorized into pure fuzzy classifiers and Fuzzy Rule Based Classification System (FRBCS). The fuzzy classifiers based on fuzzy clustering [13], fuzzy pattern matching [14], and fuzzy integral [15] are not suitable for the classification problem due to the normalization and performance degradation. Fuzzy Rule Based Classification System (FRBCS) has member functions and if-then rules, which are formulated by the domain experts. The classifier based on the if-then rules creates a rule base through which qualitative reasoning is done or predicting the results. During the absence of domain experts, fuzzy rules are obtained from the training data space. The relation between the input and the output values is established using if-then rules [16]. In high dimensional data space, process of extracting fuzzy rules from the data space is considered as a search problem as every point specifies a set of rules, system behavior, and membership function [1]. To deal with uncertainty and ambiguity, the Fuzzy Rule-Based Systems utilizes linguistic variables [17]. The learning models are generated using the fuzzy rules for data classification and they develop Knowledge Base (KB) through improved convergence. Due to their simplicity and accuracy, fuzzy based classification systems are mostly suggested for imbalanced data classification [18]. In this paper, a hybrid data classification model is developed using deep learning approach, Adaptive Lion Fuzzy System (ALFS), and Robust Grey wolf based Sine Cosine Algorithm based Fuzzy System (RGSCA-FS). The comprised algorithm consists of three phases.

In the first phase, the ALFS is employed for data classification. In the second phase, Robust Grey wolf based Sine Cosine Algorithm based Fuzzy System (RGSCA-FS) is used for the classification of data. The third phase uses deep learning networks for data classification. Thus, the output from three phases will be fused together using the hybrid fusion model for which the weighed fusion will be employed.The organization of the paper is as follows: section 1 describes the data classification; Section 2 reviews the existing methods of data classification. Section 3 deliberates the proposed method, section 4 describes the results and discussion of the proposed method and finally, Section 5 concludes the paper

II. LITERATURE REVIEW

The review of the existing methods is deliberated in this section. R. Chandrasekar and Neelu Khare [1] developed a brain storm fuzzy system, using the traditional fuzzy system for rule optimization. The algorithm is developed using exponential model in derivation and the membership function is based on uniform distribution. Although this method has high accuracy, it needs further improvement in the classification. Y. Deng *et al.* [2] modeled a Fuzzy Deep Neural Network (FDNN) for data classification. This method used deep neural network along with fuzzy system for the classification of the data. The data classification is improved by merging the fuzzy system with the neural network. Ali Arshad *et al.* [3] introduced a Distanced based Fuzzy C-Means along with multi-intra clusters method to control redundancy for multi-class imbalance classification. The imbalance data are classified by applying re-sampling technique to improve the classification performance. However, the stability of the method to image datasets is not checked. Shuang Feng *et al.* [4] developed a Fuzzy- Deep Belief Network (Fuzzy DBN) for pre-training Fuzzy Restricted Boltzmann Machines (FRBMs) in a layer-wise manner and stacking them one on top of another. The learning procedure is divided into pre-training phase and a subsequent fine-tuning phase. The bottom FRBM is trained by original samples, and the average values of the right and left probabilities produced by its hidden units are treated as the training data for subsequent FRBM. However, this method did not have updates regarding sparsity and mean-field.

2.1Challenges

The challenges faced by the fuzzy system in data classification are:

- In the fuzzy classifier, the membership function consists of several parameters. These parameters influence the classification accuracy and hence, tuning of parameters is necessary [21][28].
- The search space of the fuzzy rules grows exponentially as the number of patterns increase thus, making the learning process complex, which causes scalability and complexity issues [19][29].
- One of the important challenges is the optimization of rules into locations, as the consideration of multiple attributes affects the performance. Thus, the length of the rule is important for rule optimization [20][30-33].
- The Exponential Brain Storm Optimization (EBSO) method optimally selects the rules for the fuzzy classifiers, but it fails to optimize the parameters of the membership function resulting in reduced classification performance [1].

III. PROPOSED HYBRID FUSION MODEL FOR DATA CLASSIFICATION

The data classification in this work is based on the hybrid fusion model that is developed using the deep learning approach, ALFS, and RGSCA-FS. ALFS use the fuzzy rules, RGSCA-FS use the principles of Grey wolf optimization (GWO) and sine cosine algorithm (SCA), and deep learning for data classification.

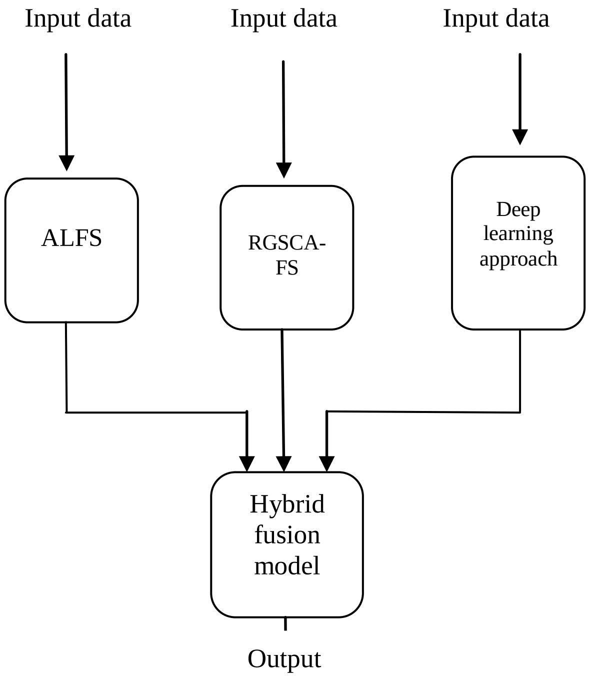

Figure 1. Block diagram of proposed hybrid fusion model

The outputs are generated individually using the afore-mentioned models, which are fused together using the weighed fusion will be employed. Figure 1 shows the hybrid fusion model for data classification.

3.1 Data classification using ALFS: Proposed fuzzy classifier for the classification

This section shows the data classification using ALFS, which is designed by adopting the proposed ALA in the rule generation. The classification is performed after the formation of fuzzy membership function and rule base in the proposed ALFS. The major components of ALFS are fuzzification, fuzzy inference, and defuzzification. In the fuzzification process, the input testing data value is converted into fuzzy value. The rule base is matched with the input by the inference. A set of rules are generated using ALA with training data as the input. The rules are represented as

$$X^S = \{X_r^S\}; 1 < v \le r ,$$

where r is the total number of rules.
According to the rule weights, the if-then rules are generated optimally.

Finally, the fuzzy score is generated using three linguistic terms, such as 'small', 'medium' and 'large' in the defuzzification process. The relation of the input with the class is described by the if-then rules and the class labels classify the input data. The data classification output derived using the ALFS is symbolized as, C_1.

3.2 Data classification using deep learning:

This method shows the classification of the data using deep learning designed by adopting ALA in rule generation. The deep learning provides better classification of the data. Deep Convolutional Neural Network (CNN) consists of three layers, such as pooling (POOL) layers, convolutional (conv) layers and a Fully Connected (FC) layers. The architecture of deep CNN is depicted in figure (2). In deep CNN, the patch of neurons from one layer is connected to the individual neurons of the next layer. The functions carried out by the Deep CNN are feature maps development in conv layers, feature map sub-sampling in POOL layers and the classification in the FC layer. The accuracy in the classification of the data is improved by increasing the number of conv layers.

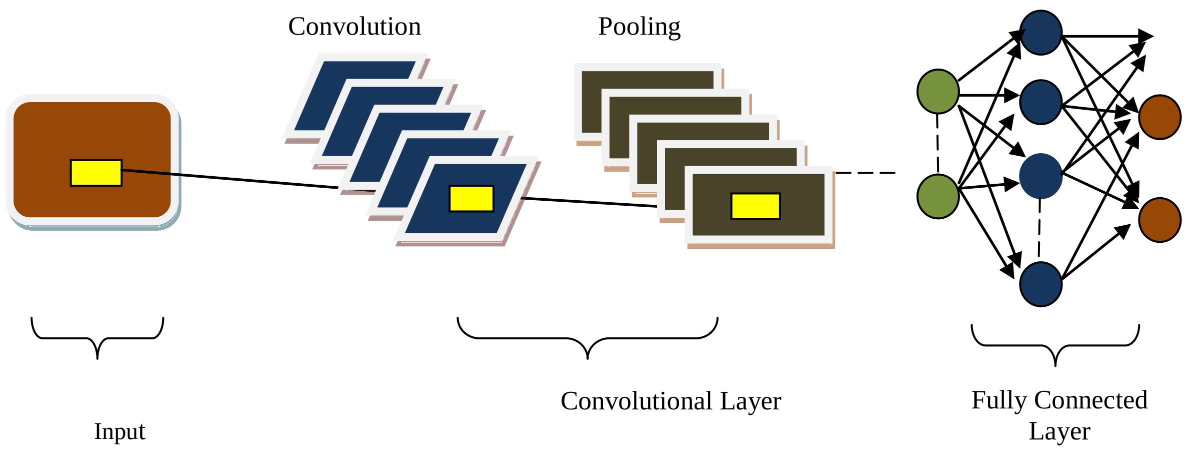

Figure 2. Architecture of Deep CNN

Convolutional layers:
The conv layer uses the conv filters to obtain the pattern buried in the input compressed signal. The receptive fields provide interconnection among the neurons of the previous layer with the successive conv layers using trainable weights and they are connected with the conv filters. For the given input C, the output of the conv layer is given as,

$$\left(D_m^b\right)_{u,v} = \left(V_m^b\right)_{u,v} + \sum_{g=1}^{g_1^{c-1}} \sum_{\beta=g_1^b}^{g_1^b} \sum_{p=-g_2^b}^{g_2^b} \left(\eta_{m,n}^b\right)_{p,\beta} \bullet \left(D_c^{b-1}\right)_{u+\beta,k+v} \tag{1}$$

where, $\bullet$ is the convolutional operator, the output of n^{th} conv layer that centered around (u,v) is represented as $\left(D_m^b\right)_{u,v}$. The input to the n^{th} conv layer is the output of the previous $(n-1)^{th}$ layer. Let us assume the weight and bias of the b^{th} conv layer as $\eta_{m,n}^b$ and V_m^b. Consider g, η and v are the notation that indicates the feature map that acts as output of conv filter, there are u conv layers, $(1 \le e \le u)$. The activation function of the previous $(f-1)^{th}$ layer is the output of the f^{th} ReLU layer. The element-wise activation function used by ReLU layer is expressed as,

$$C_x^y = C\ fn\left(C_X^{Y-1}\right) \tag{2}$$

POOL layers: The POOL layer is a non-parametric layer, hence the fixed operations are performed with no bias and weights.

Fully connected layers: The output of the POOL layer is the input to the FC layer. At the end of the network, the signals are transformed as a single signal. The output of the FC layer is expressed as,

$$M_x^y = \alpha\left(C_x^y\right) \text{ with}$$

$$C_x^y = \sum_{c=1}^{h_1^{c-1}} \sum_{\eta=-h_1^b}^{h_1^b} \sum_{e=-h_2^l}^{h_2^b} \left(\gamma_{x,c}^b\right)_{e,\eta} \left(C_c^{b-1}\right)_{t+\eta,l+e} \tag{3}$$

Deep CNN is trained to obtain the optimal weights using the weight values determined using SGD. The classified output acquired using the deep learning framework is denoted as, C_2.

3.3 RGSCA-FS for the data classification

The RGSCA algorithm is used for the data classification. RGSCA-FS [24] model consists of two major steps. The first step is the optimal selection of membership function and the second step is the optimal selection of fuzzy rules. The RGSCA-FS chooses the optimal membership function by modifying the GWO-SCA algorithm [23]. The GWO-SCA algorithm is the integration of the GWO and SCA algorithms.

The exploration and exploitation phases of GWO are modified by the solutions of SCA. This makes the solution adaptive for the random value. The membership function is formulated to achieve better performance and the parameters required for designing the membership function needs to be tuned. The data values mapped with the membership degree using the membership function.

The membership function is formed with several parameters and they form the shape of a curve. The training data is fed into RGSCA-FS model using the membership function. The input data test value is given as the input to the RGSCA algorithm that is converted into fuzzy sets. The fuzzy rules are generated using ALA [22] based on rules that is generated using optimal membership function. The generated fuzzy rules are fed into inference block. Once the training data arrives at the fuzzifier, the data is subjected to fuzzification and provided to the inference block. The rules in the rule base are in 'if-then' form for making the decision effectively. The decisions are made by the inference block, which is based on generated rules and provided to the defuzzifier. The actual fuzzy score is provided to the defuzzifier. The fuzzy score consists of the linguistic terms, such as small, medium, and large. The linguistic terms related the input test data with the output class label, thus identifying the output class label for the input data. Thus, the RGSCA-FS method classifies the data effectively using optimal membership function and the generated fuzzy rules. The data classification result from the RGSCA-FS is denoted as, C_3.

3.4 Hybrid fusion model of the data classification

The output of data classification using the three models, ALFS, deep learning (DCNN), and RGSCA-FS are fused together using the weighed constants w_1, w_2, and w_3, respectively. Thus, the output of the hybrid fusion model is given as,

$$O_{fused} = \frac{1}{3}\left[w_1 * C_1 + w_2 * C_2 + w_3 * C_3\right] \tag{4}$$

where, O_{fused} refers to the fused output of data classification. The weighed constants acquire the values between 0 and 1.

IV. RESULTS AND DISCUSSION

The result and discussion of the proposed hybrid fusion model for data classification are discussed in this section.

4.1 Experimental setup

The dataset used for the experimentation are taken from UCI machine learning repository. Three datasets, such as Statlog [25] (Australian credit approval), heart disease [26], and lung cancer datasets [27], are utilized for the experimentation.

4.2 Performance metrics

The performance metrics considered for the evaluation of the proposed hybrid fusion model over the existing approach are sensitivity, specificity, and accuracy. Sensitivity and Specificity is the proportion of positives and negatives that are correctly identified in the classification results. Accuracy is the proportion of degree of trueness in true positives or true negatives.

4.3 Comparative methods

The performance of the proposed hybrid fusion model is compared with the existing methods, such as ALFS, RGSCA-FS.

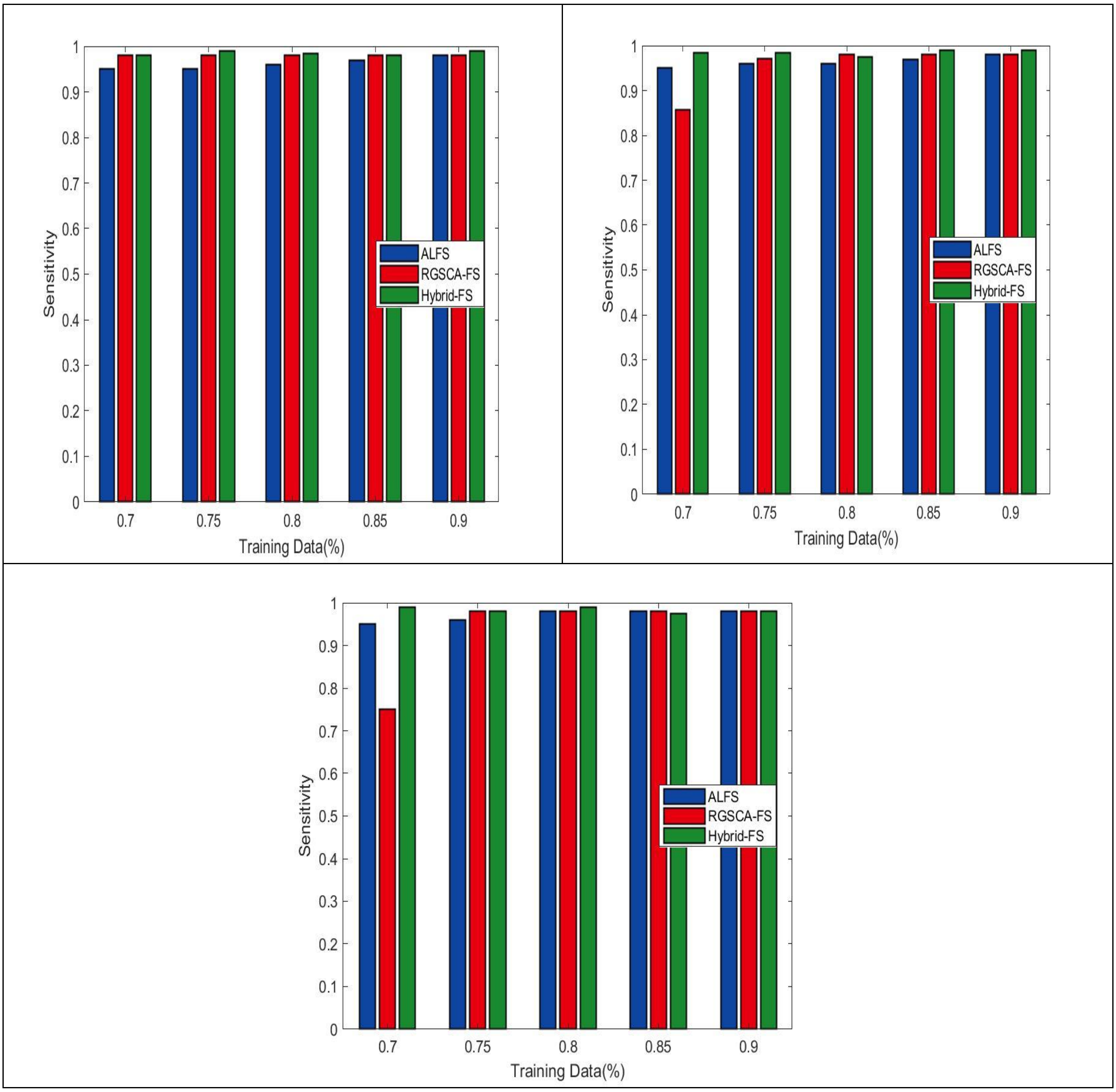

Figure 3. Analysis based on sensitivity using (a) dataset 1, (b) dataset 2, (c) dataset 3

4.4 Comparative analysis

The comparative analysis is done for the proposed hybrid fusion model and the existing ALFS, RGSCA-FS methods based on sensitivity, specificity and accuracy.

4.4.1 Comparative Analysis based on sensitivity

Figure 3 shows the analysis of the comparative methods based on sensitivity. Three datasets are

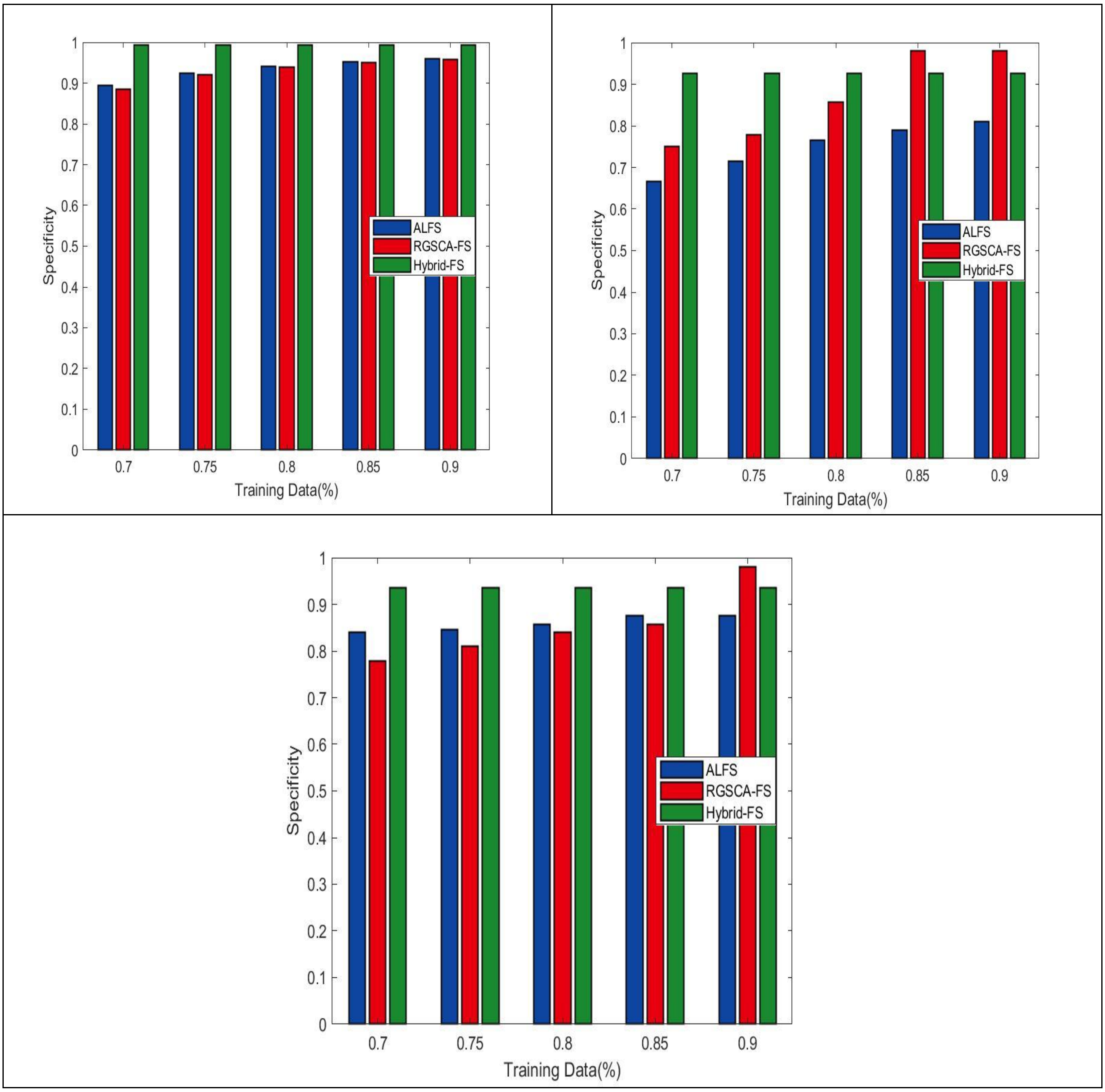

Figure 4. Analysis based on specificity using (a) dataset 1, (b) dataset 2, (c) dataset 3

analyzed by varying the percentage of training data as 70, 75, 80, 85 and 90. Figure 3 a) shows the analysis of dataset1 based on sensitivity. The sensitivity increases as the percentage of data increases. For 70% data, the sensitivity attained by proposed hybrid-FS and the existing ALFS, RGSCA-FS methods are 0.98, 0.95 and 0.98, which increases to 0.99, 0.98 and 0.98 for a maximum percentage of data. Figure 3 b) depicts the analysis of dataset2 based on sensitivity. For 70% data, the sensitivity attained by proposed hybrid-FS and the existing ALFS, RGSCA-FS methods for dataset2 are 0.985, 0.95 and 0.857, which increases to 0.99, 0.98 and 0.98 for a maximum percentage of data. Figure 3 c) shows the analysis of dataset3 based on sensitivity. For 70% data, the sensitivity attained by proposed hybrid-FS and the existing ALFS,

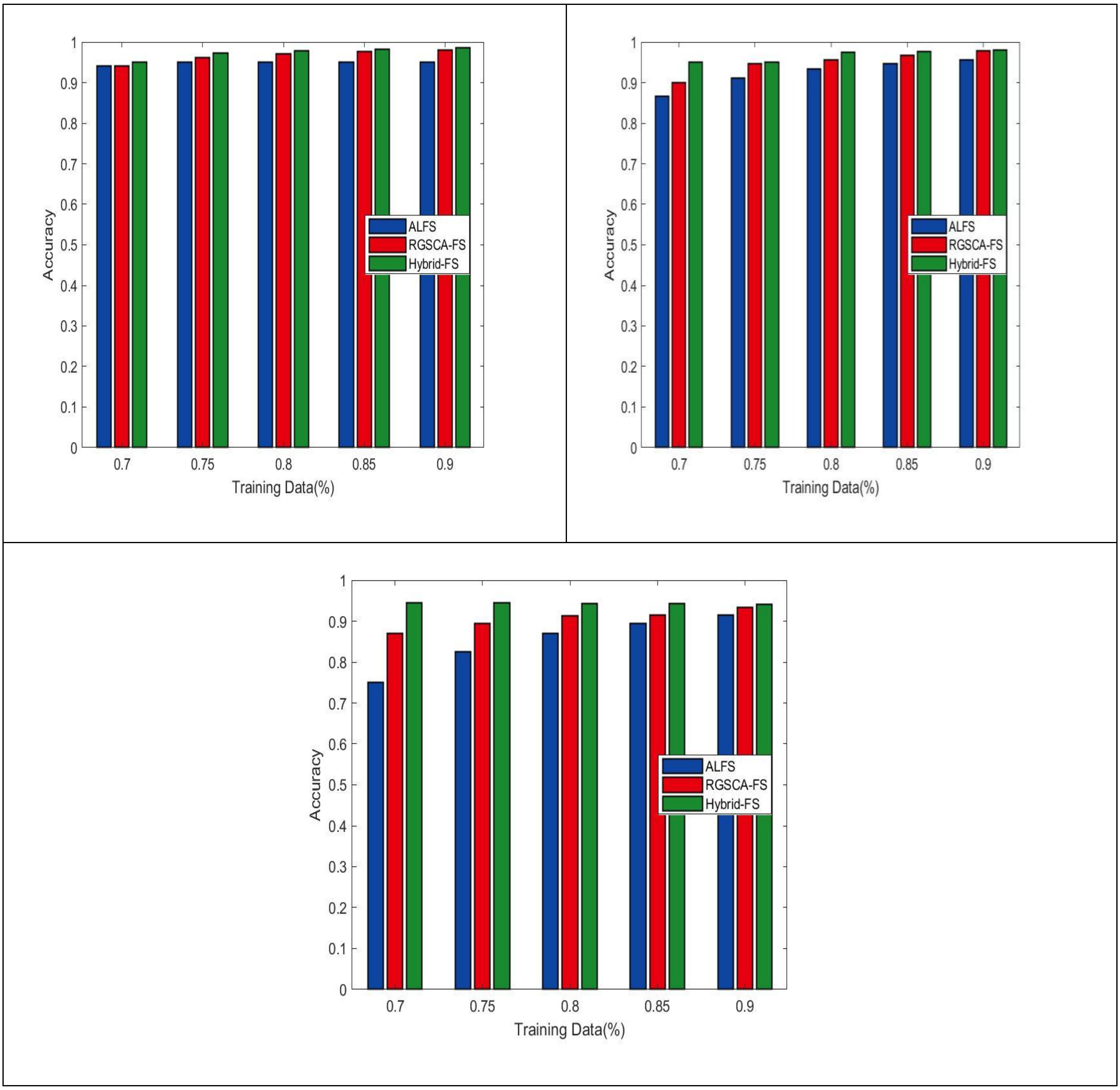

Figure 5. Analysis based on accuracy using (a) dataset 1, (b) dataset 2, (c) dataset 3

RGSCA-FS methods for dataset 3 are 0.99, 0.95 and 0.75 respectively.

4.4.2 Comparative Analysis based on specificity

Figure 4 shows the analysis carried out based on specificity using three datasets. Figure 4 a) shows the analysis based on specificity using dataset 1. The specificity increases as the training percentage increases. The specificity attained by the proposed hybrid-FS and the existing ALFS, RGSCA-FS methods for the dataset 1 at training data 70% is 0.993569132, 0.8947 and 0.885714286, which increases to 0.993569132, 0.9596 and 0.958333333 for maximum training percentage. Figure 4 b) depicts the analysis based on specificity using dataset 2. For 70% training data, the specificity for the proposed hybrid-FS and the existing ALFS, RGSCA-FS methods are 0.925925926, 0.6667 and 0.75, which increases to 0.985925926, 0.8095 and 0.98 for a maximum training percentage. Figure 4 c) shows the analysis based on specificity using dataset 3. The specificity for the proposed hybrid-FS and the existing ALFS, RGSCA-FS methods for training data 70% is 0.935064935, 0.84 and 0.777777778, which increases to 0.935064935, 0.875 and 0.98 for maximum training percentage.

4.4.3 Comparative Analysis based on accuracy

Figure 5 shows the analysis of the comparative methods based on accuracy. Three datasets are analyzed by varying the percentage of training data as 70, 75, 80, 85 and 90. Figure 5 a) shows the analysis of dataset1 based on accuracy. The accuracy increases as the percentage of data increases. For 70% data, the accuracy attained by proposed hybrid-FS and the existing ALFS, RGSCA-FS methods are 0.95, 0.942 and 0.9420, which increases to 0.9866, 0.95 and 0.98 for a maximum percentage of data.

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Figure 5 b) depicts the analysis of dataset 2 based on accuracy. For 70% data, the accuracy attained by proposed hybrid-FS and the existing ALFS, RGSCA-FS methods for dataset 2 are 0.95, 0.8667 and 0.9, which increases to 0.9804, 0.9556 and 0.9777 for a maximum percentage of data. Figure 5 c) shows the analysis of dataset 3 based on accuracy. For 70% data, the accuracy attained by proposed hybrid-FS and the existing ALFS, RGSCA-FS methods for dataset 3 are 0.945383002, 0.75 and 0.870967742, which increases to 0.9411, 0.9149 and 0.9333 for a maximum percentage of data.

V. CONCLUSION

In this paper, a hybrid data classification model is developed for data classification. This method consists of three stages of data classification. The first stage uses ALFS, the second stage uses Robust Grey wolf based Sine Cosine Algorithm based Fuzzy System (RGSCA-FS) and the third stage uses deep learning networks for data classification. The outputs from the three stages are fused together using a weighted fusion to form a hybrid fusion model. Three different datasets extracted from UCI machine learning repository is used for validating the performance of the system. Comparative analysis is done with the existing method to prove the efficiency of the proposed method. The performance analysis is done using the metrics, such as sensitivity, specificity and accuracy, which outperforms the existing methods with sensitivity of 0.99, specificity of 0.935064935, and accuracy of 0.941129032 respectively. This method can be further enhanced by developing hybrid fusion models for effective classification of data.

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