Analysis on Misclassification in Existing Contraction of Fuzzy Min–max Models

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***Abstract*—Fuzzy min–max (FMM) neural network is one of the most powerful models for pattern classification. Various models have been introduced based on FMM model to improve the classification performance. However, the misclassification of the contraction process is a crucial issue that has to be handled in FMM models to improve classification accuracy. Hence, this research aims to analyse the existence and execution procedure of addressing the misclassification of the contraction in the current FMM models. In this manner, practitioners and researchers are aided in selecting the convenient model that can address the misclassification of the contraction and improve the performance of models in producing accurate classification results. A total of 15 existing FMM models are identified and analysed in terms of the contraction problem. Results reveal that only five models can address the contraction misclassification problem. However, these models suffer from serious limitations, including the inability to detect all overlap cases, and increasing the network structure complexity. A new model is thus needed to address the specified limitations for increasing the pattern classification accuracy.**

Keywords — Patten classification, Misclassification, Fuzzy Min- Max, FMM models

I. INTRODUCTION

Artificial neural networks (ANNs) are mathematical models of artificial nodes that mimic the functions of biological neural networks, such as calculating and distributing information in the human brain [1], [2]. The first model of ANNs was proposed by McCulloch and Pitts in 1943 [3], [4]. This model aimed to emulate the biological neural structure by formulating a mathematical model of biological neurons. It consists of a group of neurons and processes that are interconnected by weighed connections to form the network structure [5].

Many attempts have been made to develop an ANN architecture for the pattern recognition problem, including multilayer layer perceptron [6], Hopfield neural network [7], [8] and radial basis function [9]. In this regard, ANN has emerged as one of the most computerised approach used for pattern recognition [10]. The combination and application of the ANN with fuzzy set method have been used to reduce the restrictive assumptions of each existing ANN method [11]. The primary aim of using the ANN along with fuzzy sets is to transform the input data into more meaningful outputs [12].

Fuzzy min–max (FMM) neural network is a neuro-fuzzy system that synthesises the role of a fuzzy set in neural networks for pattern classification [13]. The FMM model depends on the hyperbox concept, where hyperboxes are used to build the network and store knowledge. Each hyperbox has n-dimensions, which are specified by two corners called min (v) and max (w). Each hyperbox belongs to a single class.

The FMM learning stage is composed of the single-pass-through and online-adaptive system that is executed within a short timeline. The pattern classification of the FMM model is conducted via three learning processes, namely, expansion, overlap test and contraction. Different models have been proposed based on the traditional FMM model to improve the pattern classification process. Examples are general FMM neural network (GFMM) [10], Inclusion/Exclusion classifier (EFC) [14], fuzzy min–max neural network classifier with compensatory neurons (FMCN) [15], data-core-based FMM neural network (DCFMN) [16] and enhanced fuzzy min–max neural network (EFMM) [17]. These models are indicated as FMM existing models [17].

The misclassification of the contraction process is a primary challenge in FMM existing models [15], [16], [18]. Misclassification in the contraction during learning execution contributes to the inability of the FMM models to produce high classification accuracy. However, the impact of misclassification of the contraction in FMM models has not been studied by many researchers. Thus, the aim of the present research is to analyse and investigate the presence of the contraction misclassification problem in current FMM models. To this end, this research discusses and reveals the execution procedure of catering the contraction misclassification problem in FMM models.

As a comprehensive source for understanding the misclassification of the contraction in existing models of FMM, this study helps the researcher and practitioners who are working on pattern classification. It is also a useful guide for selecting the convenient model for addressing the misclassification issue of the contraction and improving the classification performance.

The rest of this paper is structured as follows. Section II illustrates the methodology that is constructed to conduct this research. Section III elaborates on and discusses the findings. Section IV concludes this research and highlights future work.

II. METHODOLOGY

Methodology is an essential element that must be constructed to achieve the aim of a research [19], [20]. Thus, a methodology was designed to conduct this research and fulfil the defined objective. Figure 1 depicts the research methodology used, which comprises four concatenation phases: formulation of research questions, exploration of related research papers, analysis of the selected related research papers and results.

In the first phase, two research questions (Q) were specifically formulated based on the defined objective of this research. The constructed research questions are as follows:

- Q1: What are the available FMM models that address the misclassification of the contraction?
- Q2: How do the current FMM models (identified from Q1) address the misclassification of the contraction?

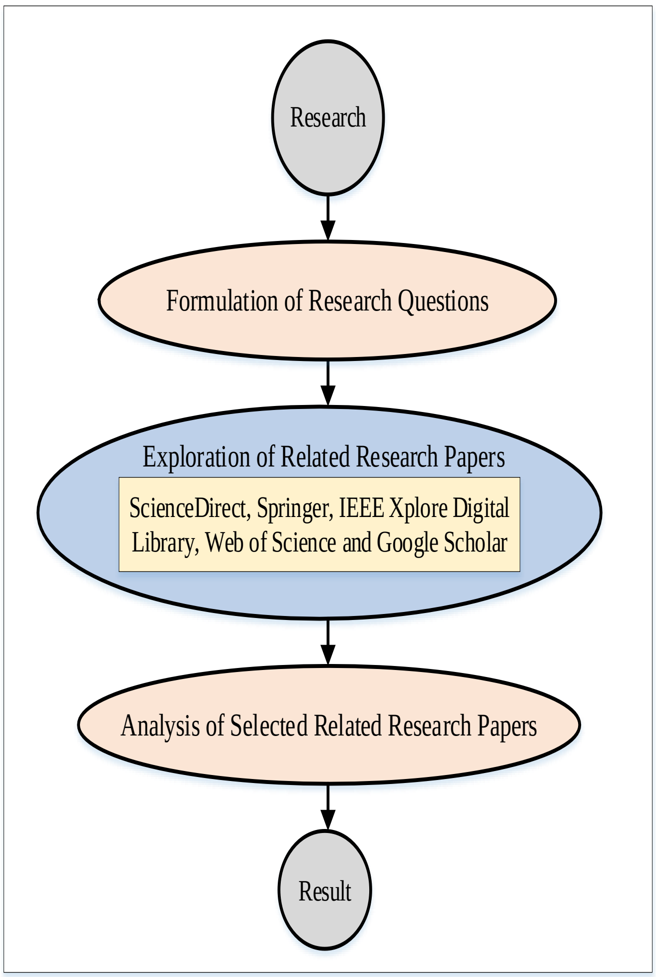

Fig. 1. Research Methodology

Moreover, on the basis of the defined research questions, exploration of the related research papers was executed by performing an online search in five digital libraries: ScienceDirect, Springer, IEEE Xplore Digital Library, Web of Science and Google scholar. These digital libraries are the most relevant to computation intelligence domain [21]. Additionally, these libraries present easy and powerful search engines, which are appropriate for automatic search of databases [21], [22].

A list of keywords was used in the search process. The keywords were specified based on the listed research questions of this work, including pattern classification, misclassification issue, OR error, OR problem, OR challenge in fuzzy min–max (FMM) pattern classification and FMM neural network, OR models and OR techniques.

Each collected research paper was then critically investigated by screening its title, keywords and abstract. Hence, studies that focus on the misclassification in FMM models' pattern classification and include at least an answer for the formulated research questions were included. The full content of each included related research paper was then studied and analysed to extract answers for the specified research questions.

III. FINDINGS AND DISCUSSION

In this section, the findings of this research is elaborated and discussed. The findings reflect the outcome of answering each formulated research question. The critical analysis of the misclassification in the existing contraction in FMM models is conducted to obtain answers for the research questions. Each FMM model is analysed in terms of its ability to solve the misclassification issues for the contraction. Table I presents the analysis result of 15 existing FMM models derived from the selected studies. The result shows that 10 existing FMM models do not handle the misclassification issue accurately for the contraction. These models are FMM [23], Stochastic FMM [24], GFMM [10], WFMM [25], MFMM [26], MFMM-GA[27], EFMM [17], M-FMM [28], EFMM2 [29] and KnFMM [30]. The limitations of these models are related to their behaviour in inheriting the limitation of the contraction of the traditional FMM model, which was adopted in their learning process [28].

The contraction of these models induces the existence of membership confusion among the overlapped regions, thereby producing misclassification in the learning phase. Contraction also leads to loss of a part of the contracted hyperboxes' information. Hence, data distortion becomes a problem [21]. However, only five models can address the contraction misclassification problem, namely EFC [14], FMNC [15], DCFMN [16], RGFMM [18] and multi-level fuzzy min–max neural network (MLF) [31].

An inclusion/exclusion classifier (EFC) is proposed to execute the pattern classification for addressing the misclassification problem of FMM [14]. The EFC introduces two types of hyperboxes: inclusion and exclusion. Inclusion hyperboxes are used to indicate the input patterns of the same class, whereas exclusion hyperboxes refer to the overlap patterns. This model successfully addresses the misclassification by using the exclusion hyperboxes to represent an overlapped region instead of an FMM contraction.

TABLE I. ANALYSIS OF EXISTING OF FMM MODELS

No	Model Name	References	Has misclassification issue in the contraction process
1	General Reflex FMM Neural Network (GRFMM)	[18]	No
2	New Hyperbox Selection Rule and a Pruning Strategy for EFMM (EFMM2)	[29]	Yes
3	Enhanced Fuzzy Min-Max Neural Network (EFMM)	[17]	Yes
4	Data-Core-based Fuzzy Min-Max Neural Network (DCFMN)	[16]	No
5	FMM with Compensatory Neuron (FMCN)	[15]	No
6	Fuzzy Min-Max Neural Network Classification (FMM)	[23]	Yes
7	General FMM Neural Network (GFMM)	[10]	Yes
8	Improving FMM with a K-nearest (KnFMM)	[30]	Yes
9	Inclusion/Exclusion Fuzzy Hyperbox Classifier (EFC)	[14]	No
10	Modified FMM (MFMM)	[26]	Yes
11	Modified FMM with Genetic Algorithm (MFMM-GA)	[27]	Yes
12	Modified Fuzzy Min-Max with Mixed Attributes (M-FMM)	[28]	Yes
13	Multi-Level Fuzzy Min-Max (MLF)	[31]	No
14	Stochastic FMM Neural Network (Stochastic FMM)	[24]	Yes
15	Weighted FMM Neural Network (WFMM)	[25]	Yes

Additionally, utilising the exclusion hyperboxes assists in reducing the learning algorithm from three processes (expansion, overlap test and contraction) to two processes (expansion and overlap test). However, Reference [10] reported that the number of inclusion/exclusion hyperboxes affect the model performance by increasing the network structure complexity.

Another model that can solve the misclassification issue is the FMCN. This model can perform the pattern classification process on the basis of the traditional FMM model [15]. In this model, the misclassification issue is handled by introducing compensatory neurons (CNs) for use in the learning phase instead of FMM hyperbox contraction.

The CNs are composed of two sections: containment compensation neuron (CCN) and overlap compensation neuron (OCN). These sections are activated whenever the test sample falls into the overlap areas between hyperboxes from different classes. During the learning phase, one node is added in the compensation section for each overlapped region created. Two outputs relate to each OCN node. However, only one of these outputs is selected. Meanwhile, the CCN node has one output. The experimental result of Reference [15] showed that the classification performance of FMCN is better than that of traditional FMM. However, FMCN failed to use the suitable membership function for compensatory nodes. Thus, the samples that fall in the overlapped areas between two different classes cannot be classified correctly [31]. Moreover, this model did not execute the expansion process in case any overlap is caused by the hyperbox that expanded with other existing hyperboxes of different classes. As a result, the network structure became complex because of the increasing number of nodes in the network hidden layer [16].

A general reflex FMM neural network (GRFMM) was likewise proposed based on the GFMM model [18]. This model combines the algorithms of FMM classification and clustering in a unified framework along with the human reflex mechanism concept. The reflex mechanism is used to solve the overlap between the hyperboxes to avoid the misclassification problem instead of using FMM contraction.

The reflex mechanism is comprised of compensatory neurons, which assist to approximate the complex data topology. Compensatory neurons are divided to OCNs and CCNs. During the training phase, compensatory neurons are added dynamically to the reflex mechanism. The experimental results of this model showed the efficiency of its performance on real datasets is better than that of the GFMM model. In addition, this model can specify the underlying data structure. However, the overlap test rules used in this model are insufficient to reveal all overlap cases [17].

A DCFMN model for pattern classification was documented in [16]. The misclassification issue was the primary motivation for this model, which uses compensatory neurons to overlap a region of hyperboxes from different classes, such as FMCN. The difference between DCFMN and FMCN is that the former is composed of two types of neurons: overlapping neurons (OLNs) and classifying neurons (CNs). OLNs are used to address all types of overlap areas of different classes, whereas data patterns are classified by using CNs. A new membership function is used to consider the data characteristics and the impact of noise. The membership function contains three factors: geometric centre of the hyperbox, data core and noise. A new learning approach is introduced in this model as well, where the overlap test process starts to investigate the overlap after creating/expanding the hyperboxes for all the training data. Although this model can avoid the misclassification issue in its learning process, the overlap test rules used cannot discover all overlapped cases efficiently [17].

Furthermore, in [31], the MLF was introduced for pattern classification. This model successfully addresses the misclassification of the traditional FMM by using a multi-level structure. The MLF employs different small hyperboxes with separate classifiers in the network to handle the samples that fall in the overlapped area instead of using FMM contraction.

During the training stage in the MLF model, each node is considered a separate classifier and has two segments: hyperboxes segment (HBS) and overlap boxes segment (OLS). HBS is used to create and adjust hyperboxes into the early training phase, while OLS is used to classify the samples that fall in the overlapped zones. The outputs of separate classifiers are integrated to form the ultimate output in the network. On the basis of the experiment conducted in [31], the misclassification of the MLF model is less than that of the traditional FMM model. However, the used overlap test rules are insufficient to specify all overlapping cases. This situation affects the classification accuracy in the MLF model [17], [21].

IV. CONCLUSION

The FMM neural network has recently emerged as one of the most useful neural networks for pattern classification purpose. The FMM has a number of important properties of the learning process, such as online learning, overlap classes, nonlinear separability, fast training and soft/hard decisions. However, the misclassification issue of contraction is considered a major challenge in existing FMM models. On this basis, this research presented a comprehensive investigation of the contraction misclassification problem in the FMM models.

To conduct this research, a research method was designed with four phases: formulation of research questions, extraction of research papers, studying and obtaining the answers from the collected related studies and result. A total of 15 FMM models were identified and analysed critically with respect to the contraction misclassification issue. The findings reveal that most FMM models cannot solve the misclassification problem of the contraction in their learning process.

Only five models can address the contraction misclassification problem, namely, EFC, FMNC, RGFMM, DCFMN and MLF. As revealed from the findings, these five models still have serious challenges with respect to network structure complexity and their inability to reveal overlapped cases. Thus, further work is required with the proposal of a new model that can address the misclassification issue. The propose model should have the ability to identify all the overlap regions between the hyperboxes of different classes and reduce the complexity of the network structure.

ACKNOWLEDGMENT

The researchers would like to express their sincere gratitude for the financial support of the University Malaysia Pahang grants (RDU180369, PGRS1803110).

REFERENCES

[1] M. Lazarevska, M. Knezevic, M. Cvetkovska, and A. Trombeva-Gavriloska, “Applications of Artificial Neural Networks in Civil Engineering,” Teh. Vjesn., vol. 21, no. 6, pp. 1353–1359, 2014.

[2] Ć. Predrag, D. Lisjak, and D. Antoli, “Regression Analysis and Neural Networks As Methods for Production Time Estimation,” Teh. Vjesn. - Tech. Gaz., vol. 18, no. 4, pp. 479–484, 2011.

[3] I. Peško, M. Trivunić, G. Cirović, and V. Muč, “A Preliminary Estimate of Time and Cost in Urban Road Construction Using Neural Networks,” Teh. Vjesn. - Tech. Gaz., vol. 3651, no. June, pp. 563–570, 1848.

[4] W. S. McCulloch and W. Pitts, “A logical calculus of the ideas immanent in nervous activity,” Bull. Math. Biophys., vol. 5, no. 4, pp. 115–133, 1943.

[5] M. Yilmaz, B. Turgut, M. Gullu, and I. Yilmaz, “Application of artificial neural networks to height transformation,” Teh. Vjesn. - Tech. Gaz., vol. 24, no. 2, pp. 443–448, 2017.

[6] G. Sampson, “Parallel Distributed Processing: Explorations in the Microstructures of Cognition,” Language (Baltim)., vol. 63, no. 4, pp. 871–886, 1987.

[7] J. J. Hopfield, “Neural networks and physical systems with emergent collective computational abilities.,” Proc. Natl. Acad. Sci., vol. 79, no. 8, pp. 2554–2558, 1982.

[8] J. J. Hopfield, “Neurons with graded response have collective computational properties like those of two-state neurons.,” Proc. Natl. Acad. Sci., vol. 81, no. 10, pp. 3088–3092, 1984.

[9] D. S. Broomhead and D. Lowe, “Radial Basis Functions, Multi-Variable Functional Interpolation and Adaptive Networks,” R. Signal Radar Establ., 1998.

[10] B. Gabrys and A. Bargiela, “General fuzzy min-max neural network for clustering and classification,” IEEE Trans. Neural Networks, vol. 11, no. 3, pp. 769–783, 2000.

[11] K. Punitha and B. Latha, “Sampling imbalance dataset for software defect prediction using hybrid neuro-fuzzy systems with Naive Bayes classifier,” Teh. Vjesn. - Tech. Gaz., vol. 23, no. 6, 2016.

[12] A. S. Loron, “An integrated fuzzy analytic hierarchy process-fuzzy data envelopment analysis (FAHP-FDEA) method for intelligent building assessment,” Teh. Vjesn. - Tech. Gaz., vol. 22, no. 2, pp. 383–389, 2015.

[13] a Joshi, N. Ramakrishman, E. N. Houstis, and J. R. Rice, “On neurobiological, neuro-fuzzy, machine learning, and statistical pattern recognition techniques.,” IEEE Trans. Neural Networks, vol. 8, no. 1, pp. 18–31, 1997.

[14] A. Bargiela, W. Pedrycz, and Masahiro Tanaka, “An inclusion/exclusion fuzzy hyperbox classifier,” Int. J. Knowledge-based Intell. Eng. Syst. - Adv. Intell. Tech. Eng. Appl., vol. 8, no. 2, pp. 91–98, 2004.

[15] A. V. Nandedkar and P. K. Biswas, “A fuzzy min-max neural network classifier with compensatory neuron architecture,” IEEE Trans. Neural Networks, vol. 18, no. 1, pp. 42–54, 2007.

[16] H. Zhang, J. Liu, D. Ma, and Z. Wang, “Data-core-based fuzzy min-max neural network for pattern classification,” IEEE Trans. Neural Networks, vol. 22, no. 12 PART 2, pp. 2339–2352, 2011.

[17] M. F. Mohammed and Chee Peng Lim, “An Enhanced Fuzzy Min-Max Neural Network for Pattern Classification,” IEEE Trans. Neural Networks Learn. Syst., vol. 26, no. 3, pp. 417–429, 2015.

[18] A. V Nandedkar and P. K. Biswas, “A general reflex fuzzy min-max neural network,” Eng. Lett., vol. 14, pp. 1–11, 2017.

[19] M. M. Ahmed and N. A. M. Isa, “Knowledge base to fuzzy information granule: A review from the interpretability-accuracy perspective,” Appl. Soft Comput. J., vol. 54, pp. 121–140, 2017.

[20] F. Hujainah, R. B. A. Bakar, M. A. Abdulgabber, and K. Z. Zamli, “Software Requirements Prioritisation: A Systematic Literature Review on Significance, Stakeholders, Techniques and Challenges,” IEEE Access, vol. 6, pp. 71497–71523, 2018.

[21] O. N. Sayaydeh, M. F. Mohammed, and C. P. Lim, “A Survey of Fuzzy Min Max Neural Networks for Pattern Classification: Variants and Applications,” IEEE Trans. Fuzzy Syst., p. 1, 2018.

[22] F. Hujainah, R. B. Abu Bakar, B. Al-haimi, and M. A. Abdulgabber, “Stakeholder quantification and prioritisation research: A systematic literature review,” Inf. Softw. Technol., vol. 102, pp. 85–99, 2018.

[23] P. K. Simpson, “Fuzzy Min-Max Neural Networks-Part 1: Classification,” IEEE Trans. Neural Networks, vol. 3, no. 5, pp. 32–45, 1993.

[24] A. Likas, “Reinforcement Learning Using the Stochastic Fuzzy Min ^ Max Neural Network,” Neural Process. Lett., vol. 13, pp. 213–220, 2001.

[25] H.-J. Kim and H.-S. Yang, “A Weighted Fuzzy Min-Max Neural Network and Its Application to Feature Analysis,” in Advances in Natural Computation, 2005, pp. 1178–1181.

[26] A. Quteishat and C. P. Lim, “A modified fuzzy min-max neural network with rule extraction and its application to fault detection and classification,” Appl. Soft Comput. J., vol. 8, no. 2, pp. 985–995, 2008.

[27] A. Quteishat, C. P. Lim, and K. S. Tan, “A modified fuzzy min-max neural network with a genetic-algorithm-based rule extractor for pattern classification,” IEEE Trans. Syst. Man, Cybern. Part ASystems Humans, vol. 40, no. 3, pp. 641–650, 2010.

[28] S. Shinde and U. Kulkarni, “Extracting classification rules from modified fuzzy min-max neural network for data with mixed attributes,” Appl. Soft Comput. J., vol. 40, pp. 364–378, 2016.

[29] M. F. Mohammed and C. P. Lim, “A new hyperbox selection rule and a pruning strategy for the enhanced fuzzy min–max neural network,” Neural Networks, vol. 86, pp. 69–79, 2017.

[30] M. F. Mohammed and C. P. Lim, “Improving the Fuzzy Min-Max neural network with a K-nearest hyperbox expansion rule for pattern classification,” Appl. Soft Comput. J., vol. 52, pp. 135–145, 2017.

[31] R. Davtalab, M. H. Dezfoulian, and M. Mansoorizadeh, “Multi-level fuzzy min-max neural network classifier,” IEEE Trans. Neural Networks Learn. Syst., vol. 25, no. 3, pp. 470–482, 2014.