FLEXIBLE ENHANCED FUZZY MIN–MAX NEURAL NETWORK MODEL FOR PATTERN CLASSIFICATION PROBLEMS

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Dalam usaha membina sebuah model pengkelas yang berkesan, pelbagai model kecerdasan pengkomputeran hibrid telah diperkenalkan. Salah satu daripadanya ialah model min-max kabur tertingkat (EFMM) yang merupakan antara model terbaru dengan berbagai ciri penting, seperti kebolehan menyediakan proses pembelajaran dalam talian dan mengendali masalah kelupaan. Meskipun EFMM terbukti sebagai salah satu model utama yang dapat mengatasi masalah klasifikasi corak, isu berkaitan proses pembelajaran, seperti pertindihan antara hiperboks, nilai pekali pengembangan rambang (takrifan pengguna) dan pengecutan hiperboks masih tidak dapat diselesaikan. Oleh yang demikian, dua peringkat pembaikan diperkenalkan dalam kajian ini untuk mengatasi batasan semasa dan menambah baik prestasi klasifikasi dari segi ketepatan dan kerumitan. Dalam peringkat pertama, satu model min-max kabur tertingkat fleksibel (FEFMM) dicadangkan untuk mengatasi batasan berhubung dengan isu ketepatan. Oleh itu, empat prosedur baharu telah diperkenalkan. Pertama, strategi latihan baru dicadangkan untuk mengelak penghasilan kawasan bertindih yang tidak perlu. Kedua, prosedur pengembangan fleksibel baharu diperkenalkan bagi menggantikan parameter takrifan pengguna (nilai pekali pengembangan) dengan parameter suai diri yang menghasilkan sempadan keputusan yang lebih tepat. Ketiga, peraturan ujian bertindih baharu digunakan ketika fasa ujian untuk mengenal pasti sebarang isu pertindihan pembendungan dan mengaktifkan proses pengecutan (jika perlu). Keempat, prosedur pengecutan baharu diperkenalkan untuk mengatasi pertindihan pembendungan dan menghindari masalah herotan data (kehilangan maklumat hiperboks). Dalam peringkat kedua, satu strategi pemangkasan diusulkan untuk mempertingkatkan prestasi model cadangan berkenaan masalah kerumitan rangkaian. Model ini dikenali sebagai strategi pemangkasan berdasarkan FEFMM (FEFMM-PS). Keberkesanan kedua-dua peringkat ini dinilai secara sistematik menggunakan beberapa set data tanda aras. Enam belas set data yang diperoleh daripada repositori pembelajaran mesin UCI telah digunakan dalam proses penilaian ini. Pemilihan set data ini adalah untuk merangkumi contoh dari pelbagai peringkat kesukaran, kelas input dan output, ciri-ciri dan juga keadaan. Prestasi FEFMM-PS dinilai menggunakan penunjuk statistik seperti kaedah bootstrap dan pengesahsahihan silang k-fold. Hasil kajian menunjukkan keberkesanan FEFMM dalam mengendalikan masalah klasifikasi corak dan memberikan prestasi ketepatan klasifikasi bermutu berbanding model-model berkaitan EFMM, FMM dan bukan FMM. Berhubung dengan FEFMM-PS, dapatan kajian mendedahkan bahawa model ini dapat menyelesaikan masalah kerumitan rangkaian dan memberikan prestasi ketepatan klasifikasi yang lebih baik berbanding FEFMM dan model lain. Model cadangan FEFMM dan FEFMM-PS boleh digunakan di beberapa sektor bidang untuk menilai kebolehgunaan model dengan lebih lanjut, seperti pengecaman muka, pengecaman penutur, pengecaman tandatangan dan klasifikasi teks.

ABSTRACT

In the attempts of building an efficient classifier model, various hybrid computational intelligence models have been introduced. Among these, the enhanced fuzzy min-max (EFMM) model was one of the most recent models coming with many essential features like the ability to provide online learning processes and handling the forgetting problem. Although EFMM has been proven to be one of the most premier models for undertaking the pattern classification problems, issues related to its learning process, concerning the overlap between the hyperboxes, random expansion coefficient value (user-defined) and hyperbox contraction remain unsolved. Therefore, two stages of improvements are introduced in this research to overcome the current limitations and improve classification performance in terms of accuracy and complexity. In the first stage, a new flexible enhanced fuzzy min-max (FEFMM) model is proposed to overcome limitations related to accuracy issue. Hence, four new procedures are introduced. First, a new training strategy to avoid generating unnecessary overlapped regions. Second, a new flexible expansion procedure to replace the expansion coefficient user-defined parameter with a self-adaptive value to produce more accurate decision boundaries. Third, a new overlap test rule is applied during the testing phase to identify any possible containment overlap case and activate the contraction process (if necessary). Fourth, a new contraction procedure to overcome the containment overlap and avoiding the data distortion problem (missing hyperbox information). In the second stage, a new pruning strategy is proposed to further enhance the performance of the proposed model in regards to overcome the network complexity problem. Hence, the resulting model is known as FEFMM-based pruning strategy (FEFMM-PS). The usefulness of both stages is evaluated systematically using a series of experiments using several benchmark datasets. Sixteen data sets are used in the evaluation process. These data sets are obtained from the UCI machine learning repository and the selection of these data sets is related to cover examples of different levels of difficulties, input and output classes, features, and a number of instances. The performance of FEFMM-PS in these experiments are then quantified using statistical measures where the bootstrap and k-fold cross-validation methods have been adopted. The results demonstrate the efficiency of FEFMM in handling pattern classification problems and providing a superior performance of classification accuracy as compared to the other network structures from the same variants such as EFMM, FMM variants and also non-FMM related models. Concerning the FEFMM-PS, the finding reveals that the model (FEFMM-PS) is able to solve network complexity problem and presents better classification accuracy as compared to FEFMM and other models from the literature. The proposed models FEFMM and FEFMM-PS can be applied in several application areas to further assess their applicability, such as face recognition, speaker recognition, signature recognition, and text classification.

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θ	User define expansion parameter
δ	Value of overlap
γ	Sensitive parameter
V	Minimum of hyperbox
W	Maximum of hyperbox
B_j	Hyperbox fuzzy set
A_h	Input pattern
n	Number of dimensions
i	Hyperbox number
T_i	Test sample
L	Small distance value

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANNs	Artificial Neural Networks
AFMN	An Adaptive Fuzzy Min-Max Neural Network Classifier Based on Principle Component Analysis and Adaptive Genetic Algorithm
CCNs	Contentment Compensation Neurons
CI	Computational Intelligence
CLN	Classifying Neurons
CNs	Classifying Neurons
DCFMN	Data-Core-Based Fuzzy Min-Max Neural Network Classification
EFC	An Inclusion/Exclusion Fuzzy Hyperbox Classifier
EFMM	An Enhanced Fuzzy Min-Max neural Network
EFMM2	A New Hyperbox Selection Rule and a Pruning Strategy for Enhanced FMM Neural Network
FMM-BSO	A hybrid Model of Fuzzy Min–Max and Brain Storm Optimization for Feature Selection and Data Classification
FEHC	Improved Data Classification using Fuzzy Euclidean Hyperbox Classifier
FEFMM	Flexible Enhanced Fuzzy Min–Max Neural Network
FMN-KC	Optimized Fuzzy Min-Max Neural Network: An Efficient Approach for Supervised Outlier Detection
FMCN	Fuzzy Min-Max Neural Network Classifier
FMM	Fuzzy Min-Max Neural Network
FMNWSM	Fuzzy Min–Max Neural Network for Learning a Classifier with Symmetric Margin
GA	Genetic Algorithm
GFMM	General Fuzzy Min-Max Neural Network
GRFMM	A General Reflex Fuzzy Min-Max Neural Network
HBS	Hyperbox Development

KnFMM	Improving the Fuzzy Min-Max Neural Network with a K-nearest
MFMCN	Modified FMM Classifier using Compensatory Neurons
MFM-GA	A Modified Fuzzy Min-Max Neural Network with Genetic-Algorithm-Based Rule Extractor for Pattern Classification
MFMM	A Modified Fuzzy Min-Max Neural Network with Rule Extraction and its Application to Fault Detection and Classification
M-FMM	Extracting Classification Rules from Modified Fuzzy Min-Max Neural Network for Data with Mixed Attributes
MLF	Multi-Level Fuzzy Min-Max Neural Network Classification
OCNs	Overlap Compensation Neurons
OLNs	Overlapping Neurons
OLS	Overlap Handling
Stochastic-FMM	Reinforcement Learning using Stochastic FMM Neural Network
WFMM	A Weighted Fuzzy Min-Max Neural Network

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