Optimisation Of Support Vector Machine Hyperparameters Using Enhanced Artificial Bee Colony Variant to Diagnose Breast Cancer

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OPTIMISATION OF SUPPORT VECTOR MACHINE HYPERPARAMETERS USING ENHANCED ARTIFICIAL BEE COLONY VARIANT TO DIAGNOSE BREAST CANCER

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ABSTRAK

Kanser payudara merupakan punca utama kematian berkaitan kanser di kalangan wanita di seluruh dunia. Pengesanan awal melalui kaedah seperti mammogram dan biopsi adalah penting dalam mengurangkan kematian yang berkaitan dengan kanser. Walau bagaimanapun, kaedah-kaedah ini rentan kepada ketidaktepatan disebabkan oleh campur tangan manusia dalam diagnosis. Pembelajaran mesin menawarkan penyelesaian kepada cabaran ini, dengan mesin vektor sokongan (SVM) menjadi pilihan popular untuk diagnosis kanser payudara kerana kekuatan dalam klasifikasi binari, yang sesuai dengan dataset yang digunakan dalam tesis ini. Prestasi SVM boleh dipengaruhi oleh hiperparameter, yang merupakan skala kernel dan dikenali sebagai parameter gamma dan regularisasi. (C). Algoritma metaheuristic diperkenalkan untuk mengoptimumkan hyperparameter. Algoritma ini dinamakan JAABC5ROC ialah peningkatan varian Koloni Lebah Buatan (ABC), JA-ABC5, dengan menggabungkan dengan kadar perubahan (ROC). Gabungan kedua-dua aspek ini boleh membantu menyeimbangkan dan meningkatkan keupayaan penyelidikan dan eksploitasi. Gabungan kedua-dua aspek ini boleh membantu menyeimbangkan dan meningkatkan keupayaan penyelidikan dan eksploitasi. Sebelum menggunakan JAABC5ROC sebagai pengoptimum untuk SVM, 10 fungsi benchmark digunakan untuk menentukan penilaian prestasi SVM. 5 benchmark yang biasa yang (Show Rosenbrok, Sphere, Step dan RS Schwefel Ridges dan RS Zekhelip) dan 5 CEC2017 benchmarks yang (Shifted and Rotated Zakharov Function, Hybrid Function 01, Composite Function 08, Composite Function 09 and Composite Function 10). JAABC5ROC dipilih untuk pengoptimuman yang lebih baik daripada hasil benchmark. Hyperparameter SVM dioptimalkan dengan iterasi 100,500,1500 dan 3000 dan merekodkan nilai. SVM-JAABC5ROC (SVM dioptimalkan oleh JAABC 5ROC) dibandingkan dengan tiga pengoptimuman (Grid search, Random Search dan Bayesian Optimisation) dan dibandingkannya dengan 5 klasifikator (Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), Naïve Bayes, Logistic Regression dan Decision Tree). Kedua-dua pengoptimum dan klasifikator menggunakan dataset Wisconsin dan Mammography. Dataset Wisconsin mempunyai 31 ciri dan 569 pesakit untuk Dataset Mammography dengan lima ciri dan 962 pesakit. Hasilnya mendedahkan bahawa SVM-JAABC5ROC mempunyai ketepatan 98.6% untuk Dataset Wisconsin dan 85.63% dalam Dataset Mammography apabila dibandingkan dengan optmiser. Untuk perbandingan klasifikator, ketepatan SVM-JAABC5ROC ialah 94.9% untuk Dataset Wisconsin dan 85.63% untuk dataset mammografi. SVM-JAABC5ROC melebihi semua tiga optimizer dan lima klasifikator dalam hal ketepatan untuk kedua-dua kumpulan data Wisconsin dan Mammography. Ini menunjukkan bahawa SVM-JAABC5ROC adalah model yang sangat berkesan untuk tugas klasifikasi pada set data ini.

ABSTRACT

Breast cancer is the leading cause of cancer-related deaths among women globally. Early detection through methods such as mammography and biopsy are crucial in reducing cancer-related mortality. However, these methods are vulnerable to inaccuracies due to human intervention in diagnosis. Machine learning offers a solution to these challenges, with support vector machines (SVM) being a popular choice for breast cancer diagnosis given its strength in binary classification, which suited well with the dataset used in this thesis. The performance of SVM can be affected by hyperparameters, which are kernel scale and known as gamma and regularization parameters (C). A metaheuristic algorithm is introduced to optimise the hyperparameters. This algorithm named JAABC5ROC is the enhancement of Artificial Bee Colony (ABC) variant, JA-ABC5 by combining with Rate of Change (ROC)\. The combination of these two aspects can assist to balance and enhance the exploration and exploitation capability. The combination of these two aspects can assist to balance and enhance the exploration and exploitation capability. Before using the JAABC5ROC as an optimizer for the SVM, a total of 10 benchmark function were used to determine its performance assessment 5 common benchmarks which are (Shows Rosenbrok, Sphere, Step and RS Schwefel Ridges and RS Zekhelip) and 5 CEC2017 benchmarks which are (Shifted and Rotated Zakharov Function, Hybrid Function 01, Composite Function 08, Composite Function 09 and Composite Function 10). The JAABC5ROC is chosen for its better optimisation from the benchmark result. The hyperparameter of the SVM is optmised with 100,500,1500 and 3000 iteration and record the value. The criterion for its performance is based on the specificity, sensitivity and accuracy. The SVM-JAABC5ROC (SVM optimised by JAABC5ROC) was compared with three optimisers (Grid search, Random Search and Bayesian Optimisation) and compared with 5 classifiers (Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), Naïve Bayes, Logistic Regression and Decision Tree). Both optimisers and classifiers employed the Wisconsin and Mammography dataset. The Wisconsin dataset has 31 features and 569 patients for Mammography dataset with five features and 962 patients. The results revealed that the SVM-JAABC5ROC has an accuracy of 98.6% for Wisconsin Dataset and 85.63% in Mammography Dataset when compared with the optmiser. For the classifier comparison the accuracy of SVM-JAABC5ROC is 94.9% for Wisconsin Dataset and 85.63% for mammography dataset. The SVM-JAABC5ROC outperformed all three optimizers and five classifiers in terms of accuracy for both the Wisconsin and Mammography datasets. This indicates that the SVM-JAABC5ROC is a highly effective model for classification tasks on these datasets.

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