2 Related Work

In the past years, a number of works have been focused on feature selections and classifications on the research of automatic music genre classifications, because music genre classification can organize large collections of digital music. However, the effectiveness of feature selections and classifications was considered few times. On the other hand, they were used widely not only in music genre classification.

Silla et al. [1] presented an analysis of the suitability of four different feature sets which are Inter-Onset Interval Histogram Coefficients(IOIHC), Rhythm Histogram(RH), Statistical Spectrum Descriptor(SSD), and MARSYAS in the context of the Automatic Music Genre Classification(AMGC). The feature selection procedures from IOIHS, RH, and SSD did not increase the classification accuracy. However, in MARSYAS, some features are present in almost every selection, showing they have strong discriminative power in the classification task. When selecting features, a Genetic Algorithm(GA) and an ensemble approach according to time and space decomposition are used. The result was compared to PCA which lost important features during the feature transformation process.

Fiebrink and Fujinaga (2006) questioned the effectiveness of the wrapper method feature selection. They tested a feature selection that provides realistic analysis for music classification. In the paper, testing results of forward selection showed lower accuracy than the result of no feature selection. This means that it is important to apply a good method in function selection.

In [3], four feature selection methods(GA, Forward Feature Selection, Information Gain, Correlation-based feature selection) and four classifiers(Decision Tree, kNN, NN, SVM) are studied to reveal the effects on each other in Indian Music. The result shows the NN was the best classifier. In addition, the feature selection strategy affects the performance of the classifier.

Genetic Algorithms to select acoustic features are also used in vehicle classification applications. Alexandre et al. [4] applied GA hybridization with an Extreme Learning Machine. The features were reduced to 22 from 66 and the accuracy increased by almost 20% compared to existing results.

Vatolkin et al. treated instrument detection as a machine learning task [5]. Also, the music genre and style recognition task applied multi-objective feature selection [6]. In both [5] and [6], S-Metric Selection Evolutionary Multi-objective Optimization Algorithm(SMS-EMOA) was used for feature selection. For classification, C4.5, Random Forest(RF), Naive Bayes(NB), and SVM were used. Except for C4.5, the three classifiers were not much quality would be lost.

A. Without Genetic Algorithm

Ginsel et al. [7] joined k-Nearest Neighbor and RF to

Structural Complexity. Structural Complexity worked well in the proposed environment, but the question remains whether it works well in environments other than small window size with specific values.

Another approach has made by Lee et al. [8]. In the study, a compact feature subset was proposed due to low computational complexity and limitation in the maximum number of acoustic features. In order to evaluate the quality of a feature subset obtained through each method, the Multi-label Naive Bayes (MLNB) classifier and holdout cross-validation were considered. The problem was that the accuracy was not higher than the conventional method (i.e. Restrictive Genetic Operator (RGA)) and the holdout cross-validation can highly be overfitted.

In [9], a multi-layer classifier based on SVM was used in classification. The results from SVM, NN, Gaussian Mixture Model(GMM), and Hidden Markov Model(HMM) were respectively 6.86%, 20.57%, 12.31%, and 11.94%. Although the SVM showed the lowest error rate, it took a long time to compute due to the poor computational efficiency on a large number of training samples.

In the work of Changsheng et al. [10], the features were extracted from Mel-Frequency Cepstral Coefficient(MFCC) and SVM and Back-Propagation Neural Network(BPNN) classified the outputs. The highest accuracy of classification was about 95%, but the local minimum problem has not been solved. Thus, BPNN needs a long training time and does not always converge.

Hybridized method of ReliefF and Sequential Forward Selection(SFS) was proposed in [11]. In the study, SFS was joined with Relief, because features that can be better classified are removed when combined with ReliefF. The proposed algorithm produces the highest accuracy, and at the same time runtime was less than SFS. However, there are disadvantages that ReliefF cannot effectively remove duplicate features and SFS cannot process a large dataset and when features are selected from the optimal feature subset, they cannot be removed anymore. The redundant data will eventually make the runtime longer.

Vatolkin (2013) [12] proposed improved supervised music classification based on multi-objective evolutionary feature selection. Although high-level and low-level feature selection showed good performance, there are problems to be solved. First, once popular songs are classified as energetic, orchestral arrangements are unconditionally classified as non-energetic. It can be solved by applying a semi-supervised method. Secondly, larger populations are required to provide enough trade-off solutions.

Krittika Leartpantulak and Yuttana Kitjaidure [13] combined feature selection using Particle Swarm Optimization(PSO) with classification using Stacking Ensemble. Although the result shows good accuracy, early convergence and increased computational complexity were not solved.

Huang et al. [14] proposed a self-adaptive harmony search algorithm to extract features locally. After selecting features, the datasets are transferred to Support Vector Machine (SVM) to be classified. However, the results do not clarify whether the accuracy is still better than global feature selection in the small datasets. Global methods assign a single score to a feature regardless of the number of classes, so it is easy to see results.

Turgut Özseven [15] proposed a novel feature selection method with three steps which are framing and windowing, feature selection based on acoustic analysis, and normalization. The study has been done due to current methods preferred in many fields that are not specific to Speech Emotion Recognition (SER). However, the success rate is proportional to the number of features so the efficiency seems ambiguous.

B. With Genetic Algorithm

Rho et al. proposed music information retrieval using GA-based relevance feedback [16]. The problem in the work is that the accuracy was almost 90% after 20 generations, but the response time increased exponentially according to the query length.

In [17], a genetic algorithm was used in the structure of NN, defining k in kNN, and the actual sound feature selection. Outputs that went through content-based classifiers were kNN(16%), NN(31%), and non-linear multi-layer perceptron(60%), and they were too low.

A study about music classification based on visual feature selection is proposed by Zottesso et al [18]. Features are firstly extracted by Local Binary Pattern texture descriptor(LBP). The outputs were then selected by GA and classified by SVM. It failed to reduce the number of features and to improve accuracy due to poor quality extracted from LBP.

Silla et al. proposed multiple feature vectors and time and space decomposition-based ensemble approach [19]. They accomplished the task using a combination of binary classifiers whose results are merged to produce the final genre label. In addition, the ensemble approach shows better classification results than NBB, DT, SVM, and Multi-layer Perceptron NN individually. But still, the result of the accuracy without feature selection classified by SVM shows the highest accuracy.

C. Hybridization of Genetic Algorithm

Ma (2019) proposed the implementation of Artificial Neural Network(ANN) and network simplification by applying network reduction techniques [20]. The same research has made by Rahman et al. (2019) with the same dataset. Rahman et al. made a difference by applying specificity and F measure, and the accuracy was higher.

In [21], features were extracted by PCA. Then, SFS and Interactive Feature Selection Algorithm(IFS) based on GA selected the features. However, upon convergence, the population increases rapidly. The performance and speed of SFS and GAFS improved, but pattern recognition problems remained, and IFS faced a front problem.

Silla et al. proposed multiple feature vectors and pattern recognition ensemble approach based on space and time decomposition [22]. In this work, the space decomposition approach based on the One-Against-All(OAA) and Round-Robin(RR) showed higher accuracy than the use of individual segments(Start, Middle, and End). J48, 3-NN, and NB increased accuracy almost by 3%, but the accuracy was still low(64.10%).

Correlation-based feature selection with a genetic search strategy was proposed in [23]. The study focused on traditional Malay music which results in an accuracy of 88.6%. However, it was only 2% higher compared to the results without feature selection. Thus, the question remains whether the strategy will be still effective when applied to Western music.

Karkavitsas proposed AMGC using hybrid GA [24]. The study is based on techniques from the fields of Signal Processing, Pattern Recognition, Information Retrieval, and Heuristic Optimization Method. kNN(k=16) was used for the classification method. Compared to the study of Li T. et al (2003), the study of Karkavitsas needed 36 features which are 6 more than those of Li's, but still, the classification accuracy was 67.6% which is 12.4% lower.

Campobello et al. [25] proposed three new multi-label classifiers with low computational complexity and a reduced number of audio features. However, the proposed classifiers differed in accuracy by up to 30% compared to existing single-label classifiers.

Murthy et al. [26] proposed a new genetic algorithm-based feature selection (GAFS). However, ANN shows fewer error values, but Random Forest (RF) results in higher accuracy. More experiments should be done to support the basis of why ANN was adopted in the study because not much training data were used.

D. Improved Genetic Algorithm

Gholami et al. proposed feature selection based on Improved Binary Global Harmony Search(IBGHS) for data classification [27]. In the work, the response time gets shorter, the speed of convergence was faster, the number of features was used less, and tried to prevent the local minimum problem. For future work, Gholami et al. will focus on modifying the IBGHS algorithm to solve the combinational optimization problem and it can be adapted to handle dynamic optimization problems.

[28] aims to effectively adapt and respond to immediate changes in users' preferences. After feature extraction, the output is used for the database of Interactive GA. However, the mutation is ignored so the result can be a local minimum. Thus, the 70 datasets were too small to train, and the number of songs that scored more than 80 after 7 repetitions did not exceed 6 out of 10 songs.

Athani et al. proposed a dynamic music recommender system using GA. It is able to identify n-numbers of users' preferences and adaptively recommend music tracks according to user preferences. Each stored data is analyzed using an Interactive GA based engine with content-based filtering. However, the accuracy was below 60% due to a lack of initial datasets and generations proceeded.

In [30], a novel feature selection which is GA with the m-feature operator(m-GA) and for classifier, Fisher-based system was proposed. M-GA showed better performance than a random search algorithm and GA. However, the difference in accuracy with GA was less than 2%.

[1] SILLA, C. N., KOERICH, A. L., & KAESTNER, C. A. A. (2009). A FEATURE SELECTION APPROACH FOR AUTOMATIC MUSIC GENRE CLASSIFICATION. International Journal of Semantic Computing, 03(02), 183–208. doi:10.1142/s1793351x09000719
[2] Fiebrink, R. and Fujinaga, I. (2006). FEATURE SELECTION PITFALLS AND MUSIC CLASSIFICATION. International Society of Music Information Retrieval.
[3] Doraisamy, S., Glozari, S., & Norowi, N. (2008). A STUDY ON FEATURE SELECTION AND CLASSIFICATION TECHNIQUES OF INDIAN MUSIC. International Society of Music Information Retrieval.
[4] Alexandre, E., Cuadra, L., Salcedo-Sanz, S., Pastor-Sánchez, A., & Casanova-Mateo, C. (2015). Hybridizing Extreme Learning Machines and Genetic Algorithms to select acoustic features in vehicle classification applications. Neurocomputing, 152, 58–68. doi:10.1016/j.neucom.2014.11.019
[5] Vatolkin, I., Preuß, M., Rudolph, G., Eichhoff, M., & Weihs, C. (2012). Multi-objective evolutionary feature selection for instrument recognition in polyphonic audio mixtures. Soft Computing, 16(12), 2027–2047. doi:10.1007/s00500-012-0874-9
[6] Vatolkin, I., Preuß, M., & Rudolph, G. (2011). Multi-objective feature selection in music genre and style recognition tasks. Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation - GECCO '11. doi:10.1145/2001576.2001633
[7] Ginsel, P., Vatolkin, I., Rudolph G. (2019). Analysis of Structural Complexity Features for Music Genre Recognition. 2020 IEEE Congress on Evolutionary Computation (CEC). doi: 10.1109/CEC48606.2020.9185540
[8] Lee, J., Seo, W., Park, J.-H., & Kim, D.-W. (2018). Compact feature subset-based multi-label music categorization for mobile devices. Multimedia Tools and Applications. doi:10.1007/s11042-018-6100-8
[9] Changsheng Xu, Maddage, N. C., Xi Shao, Fang Cao, & Qi Tian. (n.d.). Musical genre classification using support vector machines. 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings. (ICASSP '03). doi:10.1109/icassp.2003.1199998
[10] Kour, G. and Mehan, Neha. (2015).Music Genre Classification using MFCC, SVM and BPNN. International Journal of Computer Applications.
[11] Wu, M., & Wang, Y. (2015). A feature selection algorithm of music genre classification based on ReliefF and SFS. 2015 IEEE/ACIS 14th International Conference on Computer and Information Science (ICIS). doi:10.1109/icis.2015.7166651
[12] Vatolkin. I. (2013). Improving Supervised Music Classification by Means of Multi-Objective Evolutionary Feature Selection.
[13] Leartpantulak, K., & Kitjaidure, Y. (2019). Music Genre Classification of audio signals Using Particle Swarm Optimization and Stacking Ensemble. 2019 7th International Electrical Engineering Congress (iEECON). doi:10.1109/ieecon45304.2019.8938995
[14] Huang, Y.-F., Lin, S.-M., Wu, H.-Y., & Li, Y.-S. (2014). Music genre classification based on local feature selection using a self-adaptive harmony search algorithm. Data & Knowledge Engineering, 92, 60–76. doi:10.1016/j.datak.2014.07.005
[15] Özseven, T. (2019). A novel feature selection method for speech emotion recognition. Applied Acoustics, 146, 320–326. doi:10.1016/j.apacoust.2018.11.028
[16] Rho, S., Hwang, E., & Kim, M. (2007). Music Information Retrieval Using a GA-based Relevance Feedback. 2007 International Conference on Multimedia and Ubiquitous Engineering (MUE'07). doi:10.1109/mue.2007.161
[17] Serwach, M., & Stasiak, B. (2016). GA-based parameterization and feature selection for automatic music genre recognition. 2016 17th International Conference Computational Problems of Electrical Engineering (CPEE). doi:10.1109/cpee.2016.7738724
[18] Zottesso, R. H. D., Costa, Y. M. G., & Bertolini, D. (2016). Music genre classification using visual features with feature selection. 2016 35th International Conference of the Chilean Computer Science Society (SCCC). doi:10.1109/sccc.2016.7836004
[19] Silla Jr., C. N., Koerich, A. L., & Kaestner, C. A. A. (2008). Feature Selection in Automatic Music Genre Classification. 2008 Tenth IEEE International Symposium on Multimedia. doi:10.1109/ism.2008.54
[20] Ma, Z. (2019).Detecting Music Genres from Music Data Set: Select Features by Genetic Algorithm, Implement an Artificial Neural Network, Simplify it And Compare with Other Works.
[21] Kim, H., Park, C., Yang, H., & Sim, K. (2006). Genetic Algorithm Based Feature Selection Method Development for Pattern Recognition. 2006 SICE-ICASE International Joint Conference. doi:10.1109/sice.2006.315742
[22] Silla, C. N., Koerich, A. L., & Kaestner, C. A. A. (2008). A Machine Learning Approach to Automatic Music Genre Classification. Journal of the Brazilian Computer Society, 14(3), 7–18. doi:10.1007/bf03192561
[23] Doraisamy, S., Golzari, S., & Norowi, N. (2008). A Study on Feature Selection and Classification Techniques for Automatic Genre Classification of Traditional Malay Music. International Society of Music Information Retrieval.
[24] Karkavitsas, G. V., & Tsihrintzis, G. A. (2011). Automatic Music Genre Classification Using Hybrid Genetic Algorithms. Smart Innovation, Systems and Technologies, 323–335. doi:10.1007/978-3-642-22158-3_32
[25] Campobello, G., Dell'Aquila, D., Russo, M., & Segreto, A. (2020). Neuro-genetic programming for multigenre classification of music content. Applied Soft Computing, 106488. doi:10.1016/j.asoc.2020.106488
[26] Srinivasa Murthy, Y. V., & Koolagudi, S. G. (2018). Classification of vocal and non-vocal segments in audio clips using genetic algorithm based feature selection (GAFS). Expert Systems with Applications, 106, 77–91. doi:10.1016/j.eswa.2018.04.005
[27] Gholami, J., Pourpanah, Farhad., & Wang, X. (2020). Feature Selection based on Improved Binary Global Harmony Search for Data Classification. Applied Soft Computing.
[28] Hyun-Tae Kim, Eungyeong Kim, Jong-Hyun Lee, & Chang Wook Ahn. (2010). A recommender system based on genetic algorithm for music data. 2010 2nd International Conference on Computer Engineering and Technology. doi:10.1109/iccet.2010.5486161
[29] Athani, M., Pathak, N., & Kham, A. (2014). Dynamic Music Recommender System Using Genetic Algorithm. International Journal of Engineering and Advanced Technology.
[30] Alexandre, E., Cuadra, L., Rosa, M., & Lopez-Ferreras, F. (2007). Feature Selection for Sound Classification in Hearing Aids Through Restricted Search Driven by Genetic Algorithms. IEEE Transactions on Audio, Speech and Language Processing, 15(8), 2249–2256. doi:10.1109/tasl.2007.905139