1. INTRODUCTION

Many consider music an essential form of entertainment [1]. The development of information technology and the popularity of music streaming platforms have changed how people enjoy and listen to music. People also increasingly classify music into specific categories called music genres. As a result, we now recognize a wide variety of music genres [2],[3]. Based on APJII data, around 35.5% of internet users in Indonesia, around 46.9 million people, listen to music online [4]. Music platforms such as Spotify, Apple Music, and Deezer allow people to access an unlimited variety of music and artists worldwide. However, with so many options, users often struggle to find songs that suit their tastes. For this reason, recommender systems have become very useful in helping them find suitable music [2]. Recommender systems have become very popular in the entertainment industry, especially music. In recommender systems, several methods can be used, such as Collaborative Filtering (CF), Content-Based Filtering (CBF), as well as a combination of both, known as a Hybrid [5],[6].

Research by Adiyar and friends [7] aims to overcome the "cold start" problem and promote lesser-known musicians by developing a content-based music recommender system that prioritizes acoustic similarities between songs without relying on external features such as genre or artist. The analysis showed that the more complex the method, the better the system performance. Random recommender has the lowest performance (mean precision@10 = 0.006, mean nDCG = 0.006), followed by the genre-based approach (mean precision@10 = 0.066, mean nDCG = 0.066), while acoustic analysis shows better results (mean precision@10 = 0.112, mean nDCG = 0.125). However, the weakness of this study lies in the low quality of the metrics. Research by Ahmed and friends [8] discussed various deep learning architectures for music genre classification, emphasizing the advantages of a modified Convolutional Neural Network (CNN) that achieved 92.7% accuracy on the GTZAN dataset. Feedforward Neural Network (FNN) is used as one of the classification models, along with other models such as CNN, Support Vector Machine (SVM), k-nearest Neighbors (kNN), and Long Short-term Memory (LSTM). This research also evaluates the performance of CNN against other models, such as RNN-LSTM, SVM, and kNN, to demonstrate the effectiveness of cutting-edge deep learning approaches in this field. In addition, it highlights the importance of feature selection strategies, using Mel-Frequency Cepstral Coefficients (MFCC) for feature extraction, and explores the applicability of such models in the development of music recommendation systems. However, the weakness of this research is that Convolutional Neural Networks (CNN) models are often considered difficult to understand in depth due to their "black box" characteristics and have limitations in terms of interpretation. In addition, conventional datasets such as GTZAN are considered to underrepresent the diversity of contemporary music genres. Therefore, it is necessary to consider using a broader and more diverse dataset to improve the model's generalization ability.

However, the weakness of this study is that the applied model is not always optimal in all situations. Research [9] discusses the application of CBF in music recommender systems. To improve the user experience in finding music, the CBF method is combined with deep Neural Networks, specifically CNN. This study tested four models with different configurations and achieved an accuracy of about 73.52%. Deep learning can potentially improve the performance of music recommender systems. However, this research has some weaknesses. One is the need for extensive computational resources to train deep Neural Network models, which can be an obstacle if resources are limited. In addition, the time-consuming training process is also a challenge, although the model can produce reasonably accurate predictions. Research by Hafidh and friends [1] discusses K-Nearest Neighbors (KNN) aimed at measuring user satisfaction using the System Usability Scale (SUS) and helping users find music that matches their preferences through a recommender system that considers user and music criteria. The KNN method is used to find K-Nearest Neighbors in music data based on lyrics to provide a relevant recommender. KNN has a simple and effective numerical classification algorithm. Although the accuracy results are not mentioned, this research focuses on measuring user satisfaction, reflected in the SUS score of 83.65 with a rating of A, which belongs to the excellent category.

Additional analysis may be required to evaluate accuracy in more detail. Research by Utomo and friends [10] discusses a music recommender system using the KNN algorithm to determine the best machine learning technique for predicting song genres and developing a cosine similarity-based system. The results showed that KNN had an accuracy of 64.9%, while Support Vector Machine (SVM) reached 77%. The cosine similarity-based recommender system obtained an average accuracy of 80% in recommending songs with similar genres. The study's weakness lies in the reliance on MFCC features, which may not cover all essential aspects for genre classification. Using KNN and SVM without PCA may reduce accuracy, as PCA can improve model performance. In addition, the dataset's size and diversity may limit the model's ability to be applied to more diverse genres.

Thus, research on music recommender systems that utilize various combinations of methods, algorithms, and classification techniques continues to evolve along with technological advancements. Ultimately, recommender systems play an important role in suggesting music that matches users' preferences.

This research contributes to utilizing the KNN approach for the initial classification of song genres, Feedforward Neural Networks (FNN) as an advanced model to improve accuracy in music genre classification, and CBF to recommend songs based on the similarity of audio features. The main focus is to develop and evaluate a song recommendation system by integrating these methods while comparing the results of various *hyperparameters* to determine the optimal model. The results include *top k accuracy* metrics for genre classification and relevant song recommendations. The best FNN model integrated with CBF in this study provides song recommendations by considering the similarity of audio features between existing songs and query items. Little research has integrated classification methods with recommendation systems, as done in this study. This research contributes to classifying music genres and enhancing the user experience through personalized recommendation systems by integrating the three approaches.

This research is divided into several sections and subsections. The second section reviews previous research addressing similar topics as well as aspects related to system design. The third section reviews the proposed methodology, focusing on the development of a recommendation system using Content-Based Filtering, KNN, and FNN approaches, complemented by some experiments as part of the evaluation. The fourth section discusses the system development process using the proposed method along with the final results obtained.