I. INTRODUCTION

In this modern era, cafe has become more than just place to enjoy coffee. They have evolved into venues where people can work, socialize, and enjoy culinary delights. Many cafes are built with a variety of attractive designs and a cozy atmosphere. In addition, the innovative food and beverage menu offered by these cafes is also a special attraction for culinary enthusiasts. In major cities like Bandung, enjoying food while gathering and chatting casually has become a lifestyle. This city is well-known for offering a variety of culinary experiences, which led into a rapidly growing number of cafes. However, this rapid development creates new challenges for consumers in selecting cafes that match their preferences. Given the variety of choices and factors influencing consumer decisions—such as types of food and drinks, atmosphere, location, and reviews from other visitors—the need for an effective recommender system for cafes in Bandung becomes increasingly urgent. These systems provide recommendations based on an individual's preferences, such as their interests in certain things. The recommender system not only aims to enhance consumer satisfaction by offering choices that best meet their needs and preferences but also helps cafe owners reach a more precise target market.

Various approaches are utilized in recommender systems, including Content-based Filtering (CB), Collaborative Filtering (CF), and Hybrid approaches. These approaches provide fairly good results in their applications, depending on the domain and the objectives they aim to achieve. However, these approaches also have drawbacks. For instance, CF encounters challenges such as the cold-start problem and data sparsity. Among these approaches, CF is widely used because it can recommend complex items more accurately and is also simple to implement. This is because collaborative filtering does not depend on automatically analyzed data and does not need specific attribute information about users or items to generate recommendations [1],[2]. However, the main drawback of using the CF method is the high level of data sparsity [3]. Therefore, alternative methods are needed to address this issue and improve performance.

Recommender systems frequently utilize single-criteria ratings as the basis for an item's overall rating, which is then used to generate recommendations. However, single-criteria ratings is inadequate for accurately capturing the complex nuances that reflect a user's preferences, potentially leading to inaccurate recommendations. This limitation arises because the suitability of recommended items may be influenced by multiple aspects, resulting in less personalized recommendations for each user [4]. For instance, when choosing a cafe, besides looking at the overall rating, users also consider aspects such as cleanliness, the taste of food and drinks, quality of service, and the atmosphere of the cafe. These numerous aspects will be considerations for users in making their choices. Subsequently, the Multi-Criteria Recommender System (MCRS) was developed, which is a technique for making recommendations by studying the more complex relationships between users and items based on various criteria [1]. MCRS shows better and more personalized prediction results than methods using single-criteria values [4],[5].

In recent years, DL has achieved success for its effectiveness in several domains such as text processing and computer vision [6]. In recommender systems, methods implementing DL have also been widely adopted. Nassar et al. [7] combined DL, specifically Deep Neural Networks, with Matrix Factorization in the development of MCRS using Collaborative Filtering. The use of Matrix Factorization is highly popular in CF due to its good accuracy and ability to handle cold-start problems [8]. In recommender systems, matrix factorization divides a large user-item rating matrix into smaller matrices in order to reveal latent features such as user preferences or user commonalities. While matrix factorization has drawbacks in modeling complex relationships between users and items, combining it with deep learning can improve its performance. Deep learning overcomes this limitation by modeling the relationship in a non-linear way [7]. By combining these two methods, they created a recommender system that is more accurate, as demonstrated by Singh et al. [5], who used Deep Matrix Factorization (DeepMF) and achieved higher accuracy compared to other traditional recommendation models. Numerous research have used a variety of techniques and models to create recommendation systems for cafes or restaurants. From user-based collaborative filtering recommender system [9] to machine learning-based recommender systems like Natural Language Processing (NLP) [10], the models and techniques employed are incredibly varied. In real life, when choosing a cafe or restaurant, people often consider several aspects to find a place that matches their preferences. Recommender systems that use only a single-criteria ratings will produce recommendations that are less personalized and aligned with user preferences because they do not cover all the desired aspects.

In these study, we proposed the use of the DeepMF method to develop a Multi-Criteria-based cafe recommender system in Bandung as proposed by Singh et al. [5] to improve the accuracy of recommendation. We choose because it has shown good performance, especially with enhancements like the use of linear regression which can improve the model's performance compared to conventional DeepMF models. This recommender system will be focused on cafes located in the Bandung area.

The paper is structured as follows: Section II provides background information and related works. Section III outlines of the DeepMF model architecture. Section IV presents our experiment's findings. Section V offers a conclusion and recommendations for further study.