INTRODUCTION

Even though people quickly access information, there are questions about the accuracy of the information, especially for tourists who might want to find culinary places [1]. One of the biggest problems for tourists on vacation in Yogyakarta is that there are so many great culinary options. It can be challenging for travelers to choose a restaurant that suits their preferences [2]. This research chose the city of Yogyakarta because the city is famous as one of the cultural and culinary centers in Indonesia, with a variety of typical and authentic traditional foods. In addition, Yogyakarta is also a tourist city that is visited by many local and foreign tourists, so the need for a culinary recommendation system is very important. Recommender systems can help tourists find culinary places and provide accurate recommendations.

Recommender systems aim to provide personalized recommendations to users [3]. In recommender systems, the system combines user preference information for different types of items [4]. This information can be explicitly obtained through user ratings or reviews or implicitly through user behavior [5].

In many cases, collaborative filtering (CF) has been shown to provide good results and accuracy in recommender systems, especially on large and complex data [6]. However, the main problem with CF is the sparsity of the matrix, as CF only evaluates a small number of entries in a large matrix [7]. There is a solution to handle these problems, namely by using matrix factorization (MF). MF solves the sparsity and scalability problems in recommender systems by decomposing the user-item interaction matrix into lower ratings, allowing the extraction of latent factors for more personalized recommendations [8]. Asani, et al [9] have developed a restaurant recommendation system that uses sentiment analysis to provide more precise and relevant suggestions. The system analyzes user reviews online to assess sentiment polarity, classifying reviews as positive, negative, or neutral by integrating sentiment analysis with machine learning techniques. This approach interprets text reviews and combines the resulting sentiment with numerical ratings of restaurants. This fusion enables the creation of personalized recommendations that more accurately reflect user sentiment. However, the method using sentiment analysis has the disadvantage of overcoming sparsity, which is highly dependent on the review condition. If there are very few or no reviews available, sentiment analysis-based systems will find it difficult to provide accurate recommendations. Therefore, MF can be more efficient in overcoming sparsity because by factorizing the user-item matrix into two smaller matrices (user-latent matrix and item-latent matrix), the system can estimate missing ratings more accurately.

Chavan, et al. [10] developed a food recipe recommendation model using Big Data datasets. They utilized three main approaches: content-based filtering, collaborative filtering, and a hybrid approach. The goal of this research is to develop a hybrid model capable of providing more precise and relevant food recipe recommendations for users. Gomathi, et al [11] conducting research in a recommender system for culinary places using content-based methods and CF, whereas content-based has some deficiencies in handling data scarcity problems because it depends on the availability and quality of content features for each item and user. Another weakness is in finding the minimum error, where the content-based method is not specifically designed for iterative optimization, making the process of finding the minimum error slower and less efficient. In the system recommendation, there is a solution to handle these problems using by MF. MF addresses sparsity and scalability challenges in recommendation systems by breaking down the user-item interaction matrix into smaller matrices, allowing for the extraction of latent factors to provide more personalized recommendations [8] .

MF has often used optimization techniques such as gradient descent (GD) and its variants, including stochastic gradient descent (SGD) and mini-batch gradient descent (MGD) [3]. The difference between SGD and GD lies in how the parameters are updated. SGD updates the parameters after processing each random data instance, whereas GD waits until the entire dataset is sequentially processed [5]. On the other hand, the difference between SGD and MGD is how to calculate gradients and update parameters. SGD calculates and updates parameters after each training example, while MGD calculates the average gradient of a small group of data (mini-batch) before updating parameters [12]. In summary, SGD has advantages over MGD in terms of faster convergence, more frequent parameter updates, and better performance when handling unstable systems and outliers [13].

SGD is an optimization algorithm that efficiently uses random subsets of data (mini-batches) to calculate gradients and update parameters, making it particularly suitable for large datasets [14]. SGD is a good choice because it is computationally efficient in handling large, sparse, and high-dimensional datasets. In addition, SGD allowed real-time recommendation while improving accuracy by generating optimal solutions and varying latent factor distributions [15].

Previous research in the field of culinary place recommendation predominantly employs memory-based collaborative filtering (CF) techniques, such as user-based and item-based CF. However, these methods have limitations in addressing data sparsity and minimizing errors, as CF typically evaluates only a small subset of entries within a large matrix. Therefore, This study develop MF and SGD as optimization algorthm because SGD is one of the most prominent algorithms [5]. Based on the comparison between SGD with GD and MGD, the advantages of SGD are faster convergence, more frequent parameter updates, better memory efficiency, more robust to outliers, and helps avoid local minimum, especially in handling sparsity values [16]. Thus, there is a need for an algorithm that can solve this problem more effectively [17]. This study develop SGD and MF as the solution to handle the problem because SGD can be used in various models to handle sparse problems and aid in finding the minimum error [18]. The result of evaluating its accuracy for the recommendation will be shown with Root Mean Squared Error (RMSE) and precision value calculation [5].

It has been mentioned that SGD is capable of being one of the algorithms of MF in recommender systems. In this paper, the authors use the MF model and SGD algorithm to recommend culinary places in Yogyakarta, with the advantages of SGD mentioned earlier. This study tested by finding the most optimal learning rate value in SGD by comparing the precision and RMSE values between SGD and MGD.

The remaining sections of this paper are organized as follows. Section 2 discusses some research related to MF and SGD in culinary place recommendations. Furthermore, Section 3 explains the methodology used such as the explanation of the system flow, the explanation of the dataset used, the explanation of the MF and SGD as optimization algorithms that this study develop and explains how the test scenario was carried out. Section 4 discusses the tests carried out on MF and SGD for culinary place recommendations. Finally, in Section 5, this study provide conclusions and future work.