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Research Article

Tchaikovsky Music Recommendation Algorithm Based on Deep Learning

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In recent years, digital music is becoming more and more popular as mobile Internet and streaming media technology advance. Traditional music indexing technology mainly uses keywords to query. To find their favorite music, people must search through the vast amount of music available on the Internet nowadays, much like hunting for a needle in a haystack. In the era of mobile Internet, people's pace of life is very fast. Devices can access the network anytime and anywhere. Users have the habit of listening to music in their daily work, study, or sports. Facing the vast music library, personalized music recommendation can help users quickly and accurately find music tracks that meet their interests, which is also the focus of current music recommendation technology. According to the characteristics of Tchaikovsky music, in this paper, we establish and build an approach that can understand situations and recommend by using the additional information of labels to describe Tchaikovsky music and realize a structure on this foundation. Through user involvement, the system can deliver services akin to network radio and complete the evaluation of the Tchaikovsky music recommendation algorithm's efficacy.

1. Introduction

Today is an era of vigorous development of the Internet, but it is also an era of information overload. People's lives are increasingly inseparable from the Internet. However, in the face of massive Internet information, manual screening has also become a problem. Recommendation system plays an important role in the process of finding useful information. At present, it has been widely used in e-commerce, social networks, multimedia entertainment, information portal, mobile location services, and other fields. Music is also very suitable as a recommended item. On the one hand, due to the massive amount of digital music and the overload caused by the rapid growth trend, on the other hand, because users sometimes do not listen to specific songs, they just want to find a kind of music that conforms to the mood and environment at that time or just want to meet the novelty and find new songs that conform to their preferences. According to the 2013 China online music market annual report, the online music market revenue reached 7.41 billion yuan, an increase of 63.2% over 2012. Among them, online music revenue accounted for nearly 60%, an increase of 140% over 2012. The number of online music users increased to 450 million, with a growth rate of 4.6% [1]. Because the Internet has become the source and marketing channel of diversified digital music, which enables people to access more music. Using search engine to search the music you want to listen to is extremely time-consuming, and user preferences will change with the situation. This dynamic factor must be considered when providing music services.

Nowadays, there are two kinds of Internet music platforms. One is online on-demand service platforms, such as QQ music, baidu music, shrimp music. The homogenization of this kind of products has been very serious, and the copyright cost of entering the industry is extremely high. The second is the radio music service platform. The biggest feature of this kind of products is to make full use of the recommendation algorithm to make customized and disorderly recommendations to users. However, people's demand for music will change very suddenly with the change of mood or environment, and the means of description is very ambiguous. Because there are few people who specialize in music, most people can only express their music through piecemeal descriptions. These have led to a more profound thinking: in the past ten years of the development of Internet music, although the sound quality is higher, the transmission rate is faster, and the interaction is more friendly, the improvement of service quality in the music field is not obvious.

North and Hargreaves pointed out that users' living conditions will affect their music preferences, but most studies on music recommendation systems focus on analyzing the attributes of music itself, users' historical data, and users' basic information, and there are few studies on contacting users' environment and state [2]. Pandora researchers pointed out at the RESYS conference that music recommendation has the following 11 characteristics: large space for items, low consumption cost, rich types of items, less time spent listening to a song, high reuse rate of items, high user enthusiasm, context related, orderly, many playlist resources, no need for user concentration, and high socialization [3]. Another study shows that there is an increasing demand for additional information in music retrieval, mainly to improve the quality of situational music retrieval [4]. Therefore, the music recommendation system with context awareness can enable users to obtain more personalized recommendation services on the growing digital music service platform.

Most of the music recommendation systems are based on collaborative filtering or content-based recommendation methods, and many improvements are based on these two methods. For example, last FM music network radio uses user tags to cluster users and then recommend them, optimizing the collaborative filtering algorithm [5]. Pandora's classification of music is mainly based on the music genome created by a group of musicians and engineers, which assists in the calculation of similarity between music and optimizes the collaborative filtering algorithm [6]. Domestic emerging music network radio stations such as Douban also imitate last FM tag system to achieve the recommended [7]. Furthermore, more websites of this kind of music service generally only use simple classification according to artists and types and user statistics to realize simple recommendation. This paper mainly has the following contributions and completes the subsequent work:

(1) The context aware music recommendation system based on neural network hybrid algorithm of deep learning is designed and implemented in three modules. The system is composed of data module that provides basic data model for deep learning, its core part hybrid algorithm module, and user interaction module using MVC architecture.

(2) The experimental scheme is designed in terms of performance, as well as, function tests. The effectiveness of the algorithm based on the deep learning approach and the influence of the scheme recommendation grounded on this procedure are verified. The outcomes have indications that the recommendation system deliberated with the scheme based on deep learning, in this paper, has a certain improvement in recommendation quality.

The remaining paper is arranged as follows. A summary of the associated works and state-of-the-art literature is provided in Section 2. In Section 3, a hybrid recommendation algorithm of Tchaikovsky piano music which is, in fact, grounded over the collaborative filtering approach and case-based reasoning is presented. In Section 4, system test and outcomes assessment are discussed. Lastly, Section 5 concludes this article along with several directions for the future research.

2. Related Work

Last FM and Pandora have started to apply the recommendation system, and the pace of music recommendation research abroad has not stopped. Baccigalupoclaudio and Plaza Enric believed that sometimes what is recommended is not just a song, but a group of carefully selected song lists. Therefore, they used case-based reasoning technology to design a system that can recommend meaningful song lists, emphasizing the relationship between songs, so as to improve the overall satisfaction of users with the output results [8]. Using social network tags, Kaminskasmarius and Riccifrancesco designed a service platform that can recommend music according to places of interest, verifying the relevance between user preferences and location [9]. Lampropoulosaristomenis and others have cascaded collaborative filtering and content-based recommendation algorithms and implemented a recommendation system to obtain corresponding recommendations by uploading music files on the mobile service platform [10]. Liqing et al. used the probability model to consider the user score as Gaussian distribution, grouped the music, and then made recommendations through collaborative filtering, which effectively alleviated the problems of nonrelevance, user bias, and cold start [11].

Dmitrybogdanov et al. obtained the user model by semantic modeling of audio content and showed user preferences explicitly to facilitate users to evaluate more intuitively [12]. Domestic research on recommendation system started late, especially in the digital music service platform, which is basically imitating some methods of foreign mainstream websites. But in academic research, there are also some new ideas. Li Ruimin and others used three methods to extract music features, establish music genome, model users' singer, region, and music feature preferences, and finally realize music recommendation in mobile applications in combination with neighbor nodes [13]. Zhang Yan et al. proposed a new method to describe music features, which simplified the original feature matrix into feature vectors, improving the efficiency of the recommendation algorithm [14]. Kongxu et al. extracted the characteristic values from the sound spectrum, converted the music into the characteristic matrix, and returned the list of the most similar n music components for recommendation by calculating the similarity between the retrieved music and the music in the database [15].

For the recommendation of situational awareness, Parkhan SAEM used fuzzy Bayesian network and utility theory to model situational information, then made corresponding recommendations, and proved the usefulness of this method through actual situation tests [16]. LEEJINCHUN and LEEJAESIK combined pervasive data mining and case-based reasoning methods to implement a recommendation system for music recommendation based on context (mainly considering the time factor here), which improves the personalized service of mobile platforms [17]. Baltrunaslinas et al. took traffic conditions and driver's status as situational information and used matrix decomposition method to model, which improved the personalization of on-board mobile music recommendation [18]. Haririnegar and others used communal dockets and identifiers in order to categorize the music topics and mine the current user's situational information from music topics through playback sequences, so as to optimize the recommendation list [19].

3. Hybrid Recommendation Algorithm of Tchaikovsky Piano Music Based on Collaborative Filtering and Case-Based Reasoning

3.1. Algorithm Analysis. The algorithm design idea proposed by Chedrawy et al. is shown in Figure 1. In this way, we can not only make use of historical records to recommend, but also guide the selection of items according to the current situation of active users. In the first stage, we first use collaborative filtering based on items to calculate the similarity and list the top n items that are consistent with the user's taste. As long as the user has evaluated at least one item, a certain output can be obtained; that is, first of all, the impact of the user's cold start problem is reduced. In the second stage, feature-based information selection method is used to extract finer grained solutions (i.e., recommendation results) from the n items screened by collaborative filtering [20]. The recombined output not only considers the user's initial preference model, but also imitates the customer's current concentration in items with certain attributes, so the recommendation is more focused.

This scheme is designed according to the idea of cascade mixing. The following discusses the specific process of hybrid recommendation algorithm design. First, we use the user item scoring data to calculate the similarity between items. The measurement method has been introduced above. Considering that the article has attributes, we need to extend the similarity to each attribute item of the article and use sim (q_i, q_j) to represent the similarity between q_i and q_j under attribute t. Each user also shows different preferences for different attributes, expressed by weight wt. In this way, the user model not only has a scoring vector $(r_{p_i,q1} r_{p_i,q2}, \ldots)$ that indicates the degree of preference for items, but also includes the tendency for each attribute $(w_{t_1}, w_{t_2}, \ldots)$. The actual similarity of items considering attributes is calculated by formula (1), where t is the attribute set selected by the user in a search [21].

The actual similarity of items is calculated by formula (1), where t exemplifies the set of attributes nominated by the customer in a search.

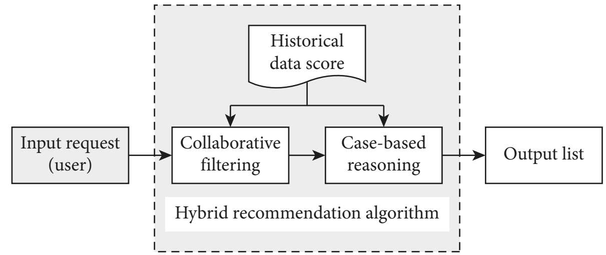

Figure 1: The algorithm design idea.

$$\operatorname{sim}\left(q_i, q_j\right) = \frac{\sum_{t\in T} w_t \cdot \operatorname{sim}_t\left(q_i, q_j\right)}{\sum_{t\in T} w_t}. \tag{1}$$

Then, in the collaborative filtering stage based on items, Top-N items will be selected rendering to the customer's preference model and the calculated resemblance of items [22]. The numerous screening steps are as follows:

(1) Find the item set Q_i that the user p_i has scored
(2) Find the K objects that are most comparable to each item in Q_i
(3) These items constitute set s
(4) Remove the items whose p_i has been scored from s
(5) Calculate the similarity between each item q_j in S and the set Q_i by weighted summation of the similarity between q_j and all items scored by the user p_i, and the weight is the scoring value
(6) Sort by the similarity between each item in s and Q_i, and output the top n items

Next, take this Top-N item as the retrieved case, and adjust the composition structure through the case-based reasoning stage. The adjustment process is to decompose the solutions of multiple groups of cases and then synthesize a composite explanation to better encounter the requirements of current active users. The decomposition process is mainly grounded on the evidence object of the issue, which is matched accurately by segments, so that each subsolution in the final solution can correspond to the customer's inclinations on each specific attribute [23]. The adjustment strategy is based on two points: (1) the first is the frequency of a subsolution in similar cases and (2) the second is the relevance between user information and cases. The steps to form a composite solution are as follows:

(1) Calculate the distance $Distc_i$ between the retrieved case c_i (i.e., items) and the user request (described as user preferences and ratings), which has been calculated in the screening step (5) of the collaborative filtering stage (i.e., the similarity between the case/item and the user's rated set)
(2) Use formula (2) to calculate the normalized distance $NDistc_i$ of case c_i under the whole search set c.

$$\mathrm{N\,di\,st}_{c_i} = \frac{1}{\mathrm{di\,st}_{c_i} \cdot \sum_{c_i\in C}\left(1/\mathrm{di\,st}_{c_i}\right)}. \tag{2}$$

(3) Determine the applicability of each subsolution. Comp is used to represent the subsolution that constitutes the initial solution, and ADComp is used to represent the applicability of the subsolution. The way to calculate ADComp is as follows: for the set c∗ that comp has appeared in the solution of case c_i, we have

$$AD_{\text{Comp}} = \sum_{c_i \in C^*} N\text{dist}_{c_i}. \tag{3}$$

(4) Integrate the subsolution comp that reaches the predetermined threshold of ADComp into the final solution. If the final solution meets the needs of users, then the new case will be saved to the original case database. Finally, after the two-stage calculation, the recommended solution not only considers the user's overall preference model, but also reflects the current user's interests.

3.2. Deep Learning Algorithm Complexity Analysis and Optimization. In the deep learning collaborative filtering stage, similarity calculation is the most time-consuming process, so the algorithm complexity of this process is mainly analyzed. Assuming that the magnitude of the scoring matrix is denoted as m∗n, where the number of users is m and the quantity of items is n, the complexity of calculating the similarity matrix of items is O(m∗n∗n∗d), and d is the data sparsity. As soon as the number of items is large, then the similarity between various items is basically $O(n^2)$. Then, the process of calculating the prediction score and listing the first n items for each user basically only needs o (m∗logn), so the efficiency of the first stage mainly depends on the similarity calculation. In the second stage, because the similarity of items calculated in the first stage is used, this part of time is saved. The main calculation focuses on the matching process between tags and tag clusters. There are K clusters, each cluster has t labels, and N' is the component numeral figure of the label vector, that is, the quantity of all items recorded with labels [24].

The complexity of calculating the similarity between the tag and the topic cluster provided by the user to describe the problem is O (k∗t∗n'∗d'), and d' is the sparsity of the tag item composition matrix. After determining the similar clusters, the cluster center vector is sorted and the proposed solution process is O (logn'). The complexity of the process of calculating the score of the proposed solution according to user preferences and forming the recommendation list of the confirmed solution by the final normalization, merging, and sorting is only related to the length of the two initial recommendation lists, so the overall and whole computational complexity of the two-stage procedure is given by O (max (m∗n∗n∗d, k∗t∗n'∗d')). That is, as soon as the number of songs is large and the total quantity of tags is essentially equal to the number of songs, then the complexity of $O\ (n^2)$ is basically presented. However, similarity calculation is generally intensive, especially for nonusers, which can be completed offline. Therefore, using distributed computing can effectively reduce computing time. Two schemes of distributed similarity calculation are given below.

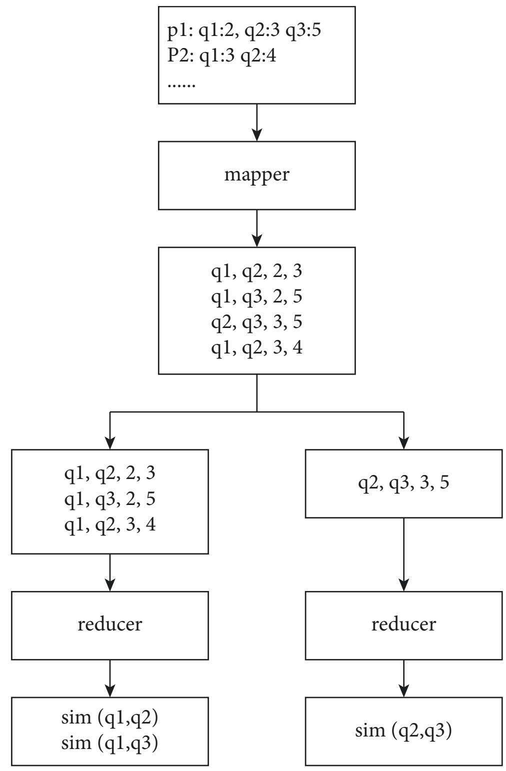

Figure 2: The schematic diagram of distributed reverse calculation process.

3.2.1. The Inverted Calculation. The specific process diagram is presented in Figure 2.

In the map phase of MapReduce, the rated items of each user are combined into *pair* < *left, right, leftscore, rightscore* > output, with left as the distribution key and *left* + *right* as the sorting key. In the reduce stage, the similarity of all items can be obtained by scanning the data from the map (this method can also be used to change the user into a label and the score into a label vector component). The advantage of this method is that there is no calculation cost of similarity between unrelated items. The disadvantage is that if some users have more scoring data, the generated pair will be very huge, and there will be a great i/o cost between mapper and reducer.

3.2.2. The Matrix Block Calculation. In the matrix block calculation approach, we cut the scoring matrix R into several small blocks, and each small block and the transposed matrix of the original matrix perform matrix multiplication operations (according to the similarity calculation formula, rather than the vector inner product) and finally merge the calculation results. The specific process diagram is shown in Figure 3, and the calculation of label similarity is similar. The advantage of this method is to avoid a large amount of cache between mapper and reducer. The disadvantage is that the transposed RT of matrix R needs to be

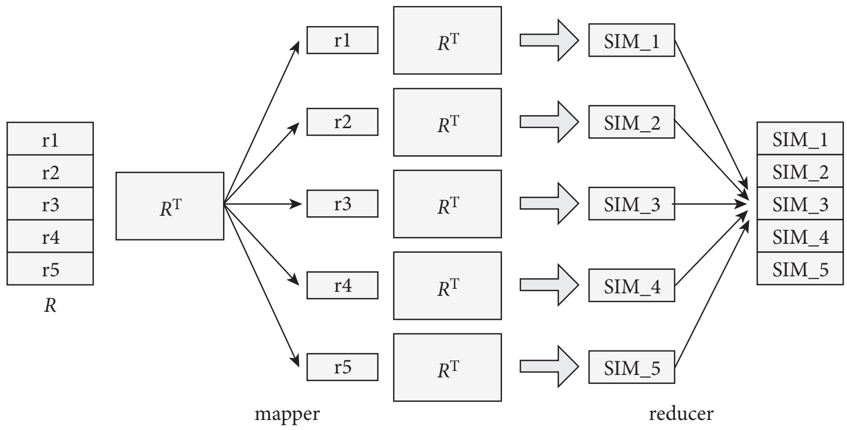

FIGURE 3: Schematic diagram of distributed matrix block calculation process.

cached in each computing node before the task starts to calculate. When the matrix R is large, it will affect the starting efficiency of the task.

The two approaches, as deliberated above, have their own benefits and shortcomings. When accurately calculating the similarity, we need to choose the appropriate calculation method according to the actual data characteristics.

4. System Test and Result Evaluation

4.1. Experimental Design and Evaluation Criteria. This paper carries out system testing in two different ways: (i) performance testing and (ii) function testing. In the performance test, we mainly distribute the public dataset into a training dataset and a testing dataset and subsequently practice the training dataset to establish the preference technique and model. In the next phase, we then use the test dataset to assess the performance of the recommendation algorithm. The assessment indicators selected in this paper are as follows:

(1) The MAE refers to the average of the absolute value of scoring error, which is generally used to measure the accuracy of scoring prediction of the recommendation system. The calculation formula is as follows:

$$\text{MAE} = \frac{1}{|R|} \sum_{r p,q \in R} \left| \hat{r}_{p,q} - r_{p,q} \right|, \tag{4}$$

where R is the total score set, $\hat{r}$ is the predicted score value, and r is the actual score value.

(2) The precision refers to the proportion of the number of highly praised items in a group of recommendations to the entire number of recommended objects. Let $R(p)$ be the list of objects that are recommended to customers, and let $\mathrm{T}(p)$ be the aggregate quantity of objects that are essentially praised by users in the test set; then, the calculation formula of accuracy is as follows:

$$\text{precision} = \frac{\sum_{p \in P} |R(p) \cap T(p)|}{\sum_{p \in P} |R(p)|}. \tag{5}$$

(3) The recall refers to the proportion of the number of items highly praised by users in a group of recommendations to the aggregate number of objects that are essentially highly praised by customers in the test dataset. It should be noted that the calculation formula is as follows:

$$\text{recall} = \frac{\sum_{p \in P} |R(p) \cap T(p)|}{\sum_{p \in P} |T(p)|}. \tag{6}$$

The system function test refers to testing the functions of each module of the system online and designing different schemes to compare the recommended effects. The environment for building the system is shown in Table 1.

4.2. Performance Test. The algorithm considered in this paper for performance comparison is the traditional collaborative filtering algorithm. The data used for offline testing is the music dataset on Tchaikovsky music. A total of 1,000 user information screened in the Tchaikovsky music group, 437,428 effective evaluation records, and 172,469 different song records are crawled. Based on these Tchaikovsky songs, 245,6821 tag records were obtained, and 254,626 valid tags were extracted. 4,566 tag topic clusters were formed by clustering, and 1,472 clusters were selected as the initial records of the case base according to the sorted vocabulary. In fact, this is vital to assess the impact of collaborative filtering under various measurement methods on the Tchaikovsky music dataset because the algorithm described in this research involves the selection of similarity measurement methods in the initial step. Figure 4 compares the MAE metric values for various training dataset proportions for the collaborative filtering stage using the Pearson and Euclidean metrics.

It can be comprehended that the forecasting score precision and correctness using the Pearson similarity are not as high as those using the Euclidean similarity. Furthermore, the prediction score error using the Pearson similarity calculation inclines to drop along with the rise and growth of the proportion of training sets, while the

Table 1: The system experimental environment.

Hardware	Servicer	Intel(R) Core(TM)2 duo CPU P7350 4G RAM 320G+500 G
Software	OS	Ubuntu 14.01
	DS	EclipseJ2EE Juno
	Servlet	Apache Tomcat 7.0.55
	Database	MySQL Server 5.6
	Algorithm AIDS	Apache Mahout0.6,Hadoop1.2.1

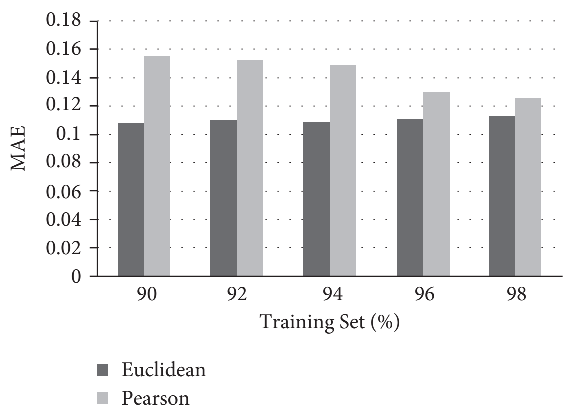

Figure 4: Assessment of forecast scoring precision using the Pearson and Euclidean similarity.

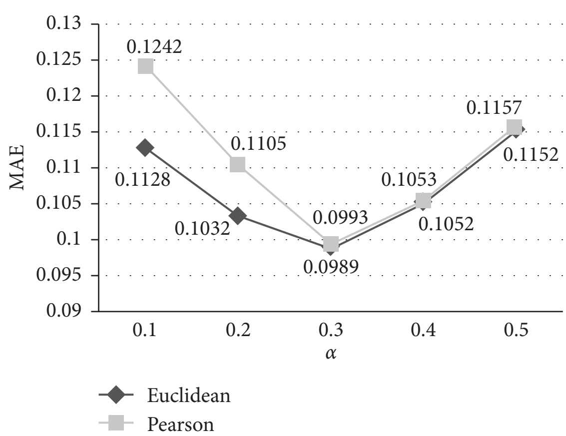

Figure 5: Different α MAE change curves of prediction score refined by case-based reasoning under parameters.

prediction score error using Euclidean similarity calculation has been increasing. Therefore, when the whole dataset is used for tangible and real recommendation, then the Pearson similarity measurement model should be more accurate. We also observed that subsequent to the second stage of filtering, the MAE rate and value fluctuations in line with the α parameter changes are given away in Figure 5.

The test shows that case-based reasoning can improve the prediction score when considering certain situational factors. Nevertheless, with the α parameters and the improvement, the extrapolation and forecast will swerve and diverge from the original customer model more and more and developed so that it is merely dependent on the recommendation of situational topics. In the collaborative filtering stage, the impact of different similarity measurement methods on the calculation of extrapolation and precision scores will also grow into less significant.

5. Conclusions and Future Research

Deep learning has been recommended in digital music for more than ten years, but how to effectively use this algorithm to recommend the music information of a composer is currently not tried by scholars, especially to solve the personalized recommendation process. Grounded on the facts and aforementioned exploration, in this paper our aim was to establish a Tchaikovsky music library, grasp user preferences through in-depth learning, and recommend Tchaikovsky music with situational bias. This paper mainly completes the following work. (1) The context aware music recommendation system based on neural network hybrid algorithm of deep learning is designed and implemented in three modules. The system is composed of data module that provides basic data model for deep learning, its core part hybrid algorithm module, and user interaction module using MVC architecture. (2) The experimental scheme is designed in terms of performance, as well as, the function tests. The effectiveness of the algorithm based on deep learning and the influence of structure of recommendation founded on this procedure are verified. The outcomes attained through empirical study express that the recommendation system that is established and built with the scheme based on deep learning in this paper has a certain, but, significant improvement in recommendation quality.

We are also investigating how to train a prediction model on the gathered dataset using learning algorithms like deep neural networks (DNNs). In that case, big data technologies like cloud and edge computing will mostly aid in storing, processing, and training the model if the data amount is large. Although the deep learning algorithms are conducted in parallel by the map reduction framework, the computational time is still constrained by the resources of a single online system. Additionally, in order to further increase the prediction accuracy, we plan to apply deep learning techniques like CNN and DNN. In actuality, the amount of data gathered to train the model has a significant impact on how accurate it is. Accuracy will increase with more data, and vice versa. Large data, however, will require a lot of computational power, which will also ensure that predictions are made in the anticipated amount of time. To increase the training efficiency in terms of computational times, big data technologies like cloud and edge computing should be leveraged.

Data Availability

The datasets used and analyzed during the current study are available from the author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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