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Non-Rating Recommender System for Choosing Tourist Destinations Using Artificial Neural Network

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***Abstract*—The development of tourist destinations in Batu City makes it hard for the tourists to decide their destinations. The recommender system is a solution that provides a lot of information or tourist attraction data. Collaborative filtering is often used in recommender systems. However, it has drawbacks; one of which is the cold-start problem, where the system cannot recommend items to new users. It was caused by the new user who had no history of rating on any item, or the system had no information. This study aims to apply a non-rated travel destination recommendation system to address the cold-start problem for new users. We use a multi-layer perceptron or artificial neural networks to overcome the problem by training user preference data to produce high training accuracy. Based on four experiments in the training data, the network architecture shows 5 – 7 – 5 – 3 – 14, which is the highest accuracy. The architecture uses five variables as inputs and three hidden layers, with each layer was activated using the ReLU activation function. The output layer produces 14 binary outputs and is activated using the sigmoid activation function. The system can give recommendations to new users using feedforward from test data with updated values in weights and biases. The test results from 46 test data showed an accuracy of 67.235%.**

***Index Terms*—Cold-start problem, artificial neural network, recommendation system, collaborative filtering.**

I. Introduction

Tourism is one of the things that can build a more advanced economic condition for Indonesia. Based on research [1], it is confirmed that, in addition to the economic sector, Indonesian tourism also maintains national identity and environmental sustainability.

In this case, East Java Province has tourist attractions that can be found in almost all cities and regencies. The attraction is the diversity and types of tourism in the form of cultural tourism, marine tourism, nature tourism, artificial tourism, and tourism developed by the creative community [2]. The number of tourist objects is one of the potentials to improve the economy of the community and the government. Batu City is a part of it. Some of the attractions in Batu City include artificial tourism, nature tourism, water tourism, culinary tourism, and historical tourism. According to [3], the newest tourist objects uploaded to social media become popular, but the other more popular objects replace them. This condition shows that more tourist attractions are updated on several social media.

This problem affects the choices of tourists, especially tourists who are going to travel to Batu City for the first time. They are confused about choosing a tourist attraction that suits their preferences. To fix the problem, a system providing information about tourism objects that suit any preferences of new tourists are needed, namely a recommender system [4]. This system is helpful for users who have many items to choose. It can predict the users' preferences for unrated items [5]. A popular approach to recommender systems is collaborative filtering. This approach provides recommendations based on the opinions of others with similar data behavior, where the assessment can be obtained directly or indirectly [6]. In some research, the indirect assessment is usually a rating value. The collaborative filtering approach has a weakness, namely the cold-start problem where there is a system problem that cannot recommend items to new users. In this research, we use a non-rating assessment and user preferences to overcome the weaknesses of the collaborative filtering approach. So, new users get recommendations for tourist destinations that match their preferences. In processing user preference data, the multi-layer perceptron type of Artificial Neural Network method is employed. A backpropagation algorithm is also used for training data to produce high accuracy.

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II. RELATED WORK

According to research [7], the model addresses the cold-start problem using the similarity among the items based on the genre of items. This research proposes a new item-based similarity metric (CatSim) and provides more accurate recommendations. The results show that CatSim is superior to other traditional similarity matrices by slightly improving the Top-N prediction, where the MAE value is ±0.66, and the precision, recall, and f-measure accuracy have a high value. Moreover, the research [8] uses social networks to understand new e-commerce users' preferences. The proposed recommender system improves the experience of new users in getting specific product recommendations on identifying user categories by analyzing their data from social networks. There are three social network elements to analyze it: direct user posts, "likes" content and "likes" pages from Twitter and Facebook, which are classified based on their characteristics using Naïve Bayes and Decision Tree. Besides, this research also applies a content-based approach. The results indicate that the RMSE value is 1.71 and has an accuracy of 40%. Previous studies used genre and social networking models to address the cold start problem. However, this research uses a non-rating assessment to get a recommender system; then, user preference data is processed with the Artificial Neural Network method.

The results of the study [9] were able to handle cold-start problems, especially cold-start systems and users, by implementing a hybrid recommendation system and aiming to predict academic choices for students. The hybrid approach in this study combines a knowledge-based approach and collaborative filtering. To overcome the problem of the cold-start system, a hybrid approach is employed to provide better recommendations and collect students' profiles explicitly. Similarity measures used in collaborative filtering for item prediction are Pearson correlation coefficient, cosine similarity, and Euclidean distance. The more efficient recommendation time is the cosine similarity, which is 14 ms, and the high precision and recall values are shown at the Euclidean distance, each yielding 0.15. Meanwhile, this research uses popular items/courses to overcome the cold-start problem of the users by considering the existing trends. Furthermore, this research considers preference variables by selecting features to get more accurate results.

III. RESEARCH METHOD

Based on Figure 1, the input stage explains that the user preference dataset is used as training data in Artificial Neural Network Method. Meanwhile, to test the recommender system using new user preference data, feedforward neural network calculations are used. Then, the process stage comprises the step to train the user preference dataset using the Artificial Neural Network method. The type of multi-layer perceptron uses the backpropagation algorithm to produce the best network architecture. The result of the network is the updated weight and bias values. These values are used in the testing process. The output stage explains the result of the system in the form of recommendations for Batu City tourist destinations to new users according to their preferences.

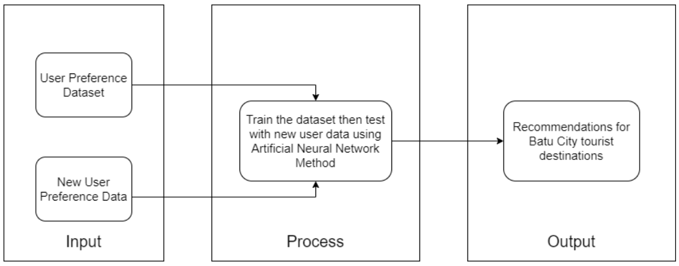

Fig. 1. System design using artificial neural network method.

A. *Recommender System*

The design in this system can recommend a product or item according to the user's wishes. Recommendations given to users are generated based on information or preferences about the user and the environment around the user. In research [10] it is explained that learning from user preferences is an interaction between items and users that can characterize them to make the recommendation system efficient.

Indeed, Collaborative filtering is an approach used in the most popular recommender system. According to [11], the collaborative filtering approach is one of the famous and successful approaches because of its simplicity and high efficiency. In this approach, the opinions or preferences given by the user can be explicit in the form of a rating and written in the form of a number interval, for example, an interval of 1 to 10. However, collaborative filtering has weaknesses; one of which is the cold-start problem. This problem occurs because the users are new users who used the system for the first time and have never given a rating or have no rating history for any item. In addition, the cold-start problem occurs because the system lacks information or data about new users, causing the system to be unable to recommend items to new users.

B. *Artificial Neural Network*

In research [12], the recommendation system is one of the branches of information retrieval and artificial intelligence. Therefore, this study uses an artificial neural network method to overcome the cold-start problem by utilizing user preference data which will be trained repeatedly to get the best network. The artificial neural network is a machine learning class model that learns complex patterns from a data set using simple mathematical functions. According to research [13], he existence of data analysis factors can provide artificial neural networks to be efficient, effective and can solve complex and non-complex problems in various fields.

On one hand, multi-layer perceptron is a derivative of a single perceptron; it is a feedforward neural network with one or more hidden layers. Based on the architecture with one or more hidden layers, a multi-layer perceptron is a complex neural network consisting of an input layer, several hidden layers, and an output layer. In the training, a multi-layer perceptron requires a backpropagation learning algorithm. Backpropagation is a gradient descent used in artificial neural networks to change the weights connected to the neurons in the hidden layer. Based on research [14], the backpropagation learning algorithm has several stages to produce the expected output, namely the feedforward stage. To produce output from feedforward, calculating training

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data from the input layer to the output layer is carried out. The second stage is the backpropagation of the error value obtained based on the calculation between the feedforward output and the actual output. The last stage is the adjustment of the weight value to minimize errors. The following is the equation of a multi-layer perceptron with one hidden layer shown in Fig. 2.

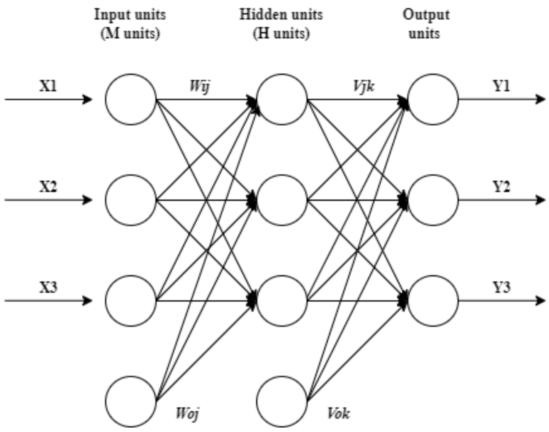

Fig. 2. Multilayer Perceptron with 1 Hidden Layer.

$$y_k = f\left(\sum_{j=1}^{H} f\left(\left(\sum_{i=1}^{M} x_i w_{i,j} w_{oj}\right) v_{j,k}\right) + v_{ok}\right) \quad (1)$$

Equation (1) is a feedforward calculation formula corresponding to Figure 1. The y_k symbol refers to the output value in the output layer. The symbol f refers to the activation function used for each layer. The symbols H and M refer to the hidden layer of units 1 and 2, where j, i, and k are the number of neurons in each layer. The x symbol refers to the input data. While the symbols w and v refer to the weight values; for bias values, the symbols w_o and v_o are used.

IV. Result

The research [15] does not use user preferences as input but uses the rating value of users who have traveled in Batu City. The research can only recommend tourist destinations to users who have previously provided a rating value in the system. User's rate 14 tourist attractions they have visited based on the 6ASTD framework to produce recommendations for tourist attractions that are suitable for users. Because the rating value is very necessary in this research, it is impossible to recommend Batu City tourist destinations to new users. Therefore, in this study, user preferences are used as input. In designing this system, questionnaires were distributed via google form and respondents were directly asked about tourist attractions. User preference data produce 227 data which is divided into 80% training data and 20% test data. In user preference data, there are also five recommendations for tourist destinations given by tourists. The data used are ten input variables (Table 1) and 14 tourism items output (Table 2).

Table. 1.
User Preference Input Variables

Input	Preferences
X1	Gender
X2	Age
X3	Profession
X4	Hobby
X5	Travel Destination
X6	Marital Status
X7	Place of Origin
X8	Travel Companion
X9	Minimum Education
X10	Repetition

Table. 2.
Tourist Destination Items

Output	Tourism Item
Y1	Jatim Park 1
Y2	Jatim Park 2
Y3	Jatim Park 3
Y4	Museum Angkut
Y5	Selecta
Y6	BNS
Y7	Eco Green Park
Y8	Alun-alun Batu
Y9	Kusuma Agrotourism
Y10	Cangar
Y11	Coban Talun
Y12	Songgoriti
Y13	Coban Rais
Y14	Predator Fun Park

According to research [16], excessive use of input variables can reduce system accuracy and system computing costs. Therefore, we need the means to minimize the input variables using the chi-square feature selection because it has good performance, especially in multiclass.

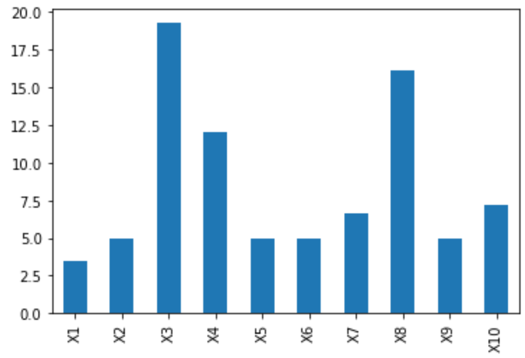

Fig. 3. Chi-square graph results.

Figure 3 shows that, of the ten inputs, there are five inputs with the highest values, namely X3 (Profession), X4 (Hobby), X7 (Place of origin), X8 (Travel companion), and X10 (Repetition). The five inputs are the inputs that have the highest correlation with the output and are the most influential ones in the classification process of the data processing of this study.

A. *Training data*

This study employs five binary inputs and 14 outputs to produce the right network and update the weight and bias values. In the process, the data is trained by changing several network architecture parameters. It aims to produce the best architecture with high training accuracy [17], [18]. The normalized training data is trained using the backpropagation learning algorithm. In addition, the number of iterations, weights, and bias values are used to produce the best network architecture and update values for weights and bias values [19], [20]. The following Fig. 4 shows the flowchart of the training process.

Based on the error graph in Figure 5, which was trained during the training process until the iteration reaches the maximum (1000 epochs), the first error or loss value with a network architecture of 5 – 1 – 5 – 4 – 14 produces 0.5504. The second loss value with a network architecture of 5 – 3 – 3 – 7 – 14 produces 0.5459. The third loss value with a network architecture of 5 – 4 – 7 – 9 – 14 produces 0.5454. And fourth loss value with a network architecture of 5 – 7 – 5 – 3 – 14 produces 0.5449. From the four losses above, it can be concluded that the minimum loss value is found in the fourth loss with a network architecture of 5 – 7 – 5 – 3 – 14.

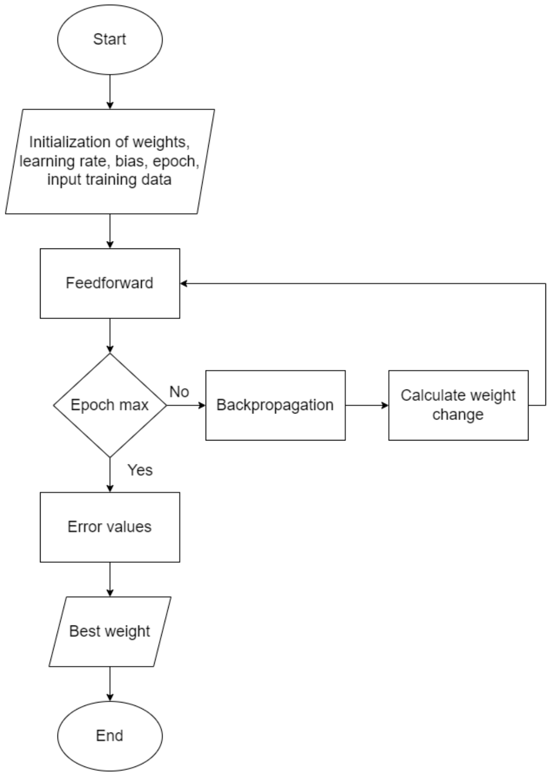

Fig. 4. Flowchart of the training process.

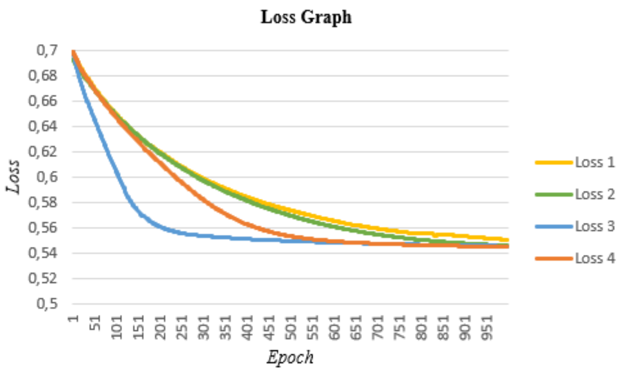

Fig. 5. Loss graph of the four training results.

Meanwhile, the result of the accuracy graph in Figure 6 during the training process until maximum iteration (1000 epochs) produces four kinds of accurate results. The first accuracy value with 5 – 1 – 5 – 4 – 14 network architecture produces 0.4514. The second accuracy value with 5 – 3 – 3 – 7 – 14 network architecture produces 0.2153. The third accuracy value with 5 – 4 – 7 – 9 – 14 network architecture produces 0.4324. And the fourth accuracy value with 5 – 7 – 5 – 3 – 14 network architecture produces 0.6597. Based on this result, the highest accuracy value is found in the fourth of 0.6597 with a network architecture 5 – 7 – 5 – 3 – 14.

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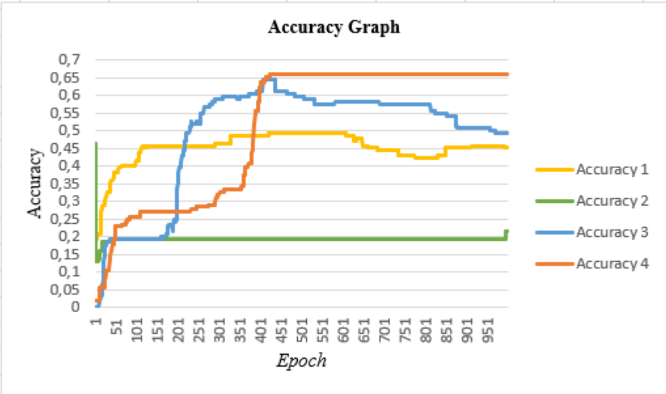

Fig. 6. Accuracy Graph of The Four Training Results

Based on the explanation above, it can be concluded that the fourth network architecture has the minimum loss value and the highest accuracy value. There are five inputs in the input layer, seven neurons in hidden layer 1, 5 neurons in hidden layer 2, 3 neurons in hidden layer 3, and 14 outputs in the output layer (5 – 7 – 5 – 3 – 14) shown in Fig. 7. The architecture will produce updated values of weights and biases to be used in the testing process to produce output recommendations for tourist destinations following new users' preferences.

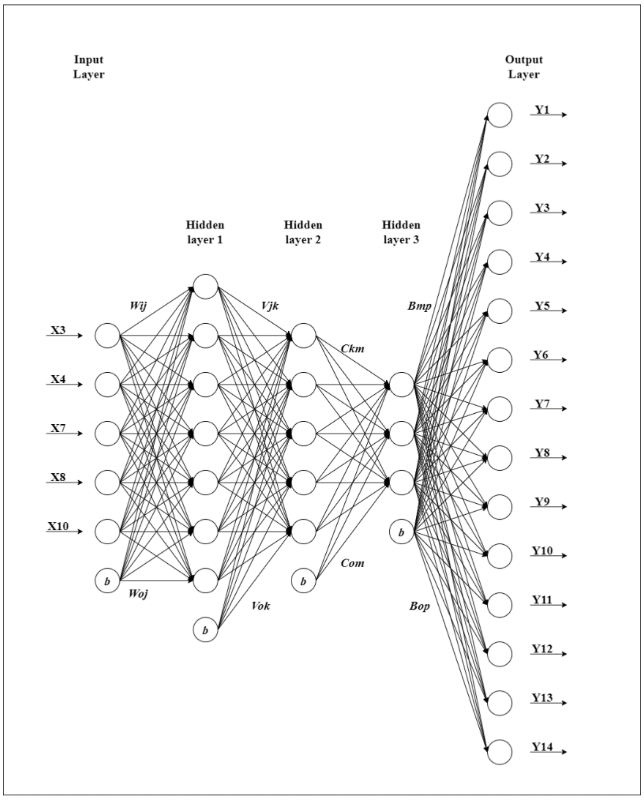

Fig. 7. Network Architecture 5 - 7 - 5 - 3 - 14.

B. Testing data

The artificial neural network method uses feedforward neural network calculations with test user data and updated values for weights and biases that have been generated in the previous training stage with a network architecture of 5 – 5 – 3 – 1 – 14. The following is Figure 8 for a flowchart of the testing process, which will enter the input value of the test data, the updated value of the weights, and biases to produce a recommendation output from the system.

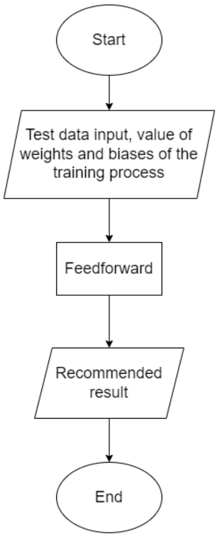

Fig. 8. Flowchart of the testing process

The following is a feedforward calculation using test data (Table 3) with updated weights and bias values obtained from the previous training process with a 5 – 7 – 5 – 3 – 14 network architecture.

Table. 3.
Test Data

Username	X3	X4	X7	X8	X10
X1	0,33	0	1	0,25	1

- Calculate output in hidden layer 1

$$Z_{in_j} = \sum_{i=1}^{5} x_i w_{ij} + w_{oj}$$

$$z_{in_1} = \big((0{,}33 \times 0{,}6760035) + (0 \times (-0{,}07473943)) + (1 \times (-0{,}6433692)) + (0{,}25 \times 0{,}6937183) + (1 \times 0{,}5857161)\big) + (-0{,}00725013) = 0{,}3316075$$

$$z_{in_2} = -0{,}060646077$$
$$z_{in_3} = 0{,}884248928$$
$$z_{in_4} = 0{,}621444843$$
$$z_{in_5} = 0{,}7331169$$
$$z_{in_6} = -0{,}57939066$$
$$z_{in_7} = 0{,}01993185$$

Apply the ReLU activation function

$$Z_j = f\left(Z_{in_j}\right) = f\left(0, Z_{in_j}\right)$$

$$z_1 = f(0, \quad 0{,}3316075) = 0{,}3316075$$
$$z_2 = f(0, \quad -0{,}060646077) = 0$$
$$z_3 = f(0, \quad 0{,}884248928) = 0{,}884248928$$
$$z_4 = f(0, \quad 0{,}621444843) = 0{,}621444843$$
$$z_5 = f(0, \quad 0{,}7331169) = 0{,}7331169$$

$z_6 = f(0, \quad -0{,}57939066) = 0$
$z_7 = f(0, \quad 0{,}01993185) = 0{,}01993185$

- Calculate output in hidden layer 2

$$T_{in_k} = \sum_{j=1}^{7} z_j\, v_{jk} + v_{ok}$$

$$t_{in_1} = \big((0{,}3316075 \times 0{,}5304773) + (0 \times 0{,}56448185) + (0{,}884248928 \times (-0{,}23397495)) + (0{,}621444843 \times (-0{,}44781088)) + (0{,}7331169 \times 0{,}02614102) + (0 \times 0{,}6180892) + (0{,}01993185 \times (-0{,}3422928))\big) + 0{,}01457165 = -0{,}28235811$$

$t_{in_2} = 0{,}03683466$
$t_{in_3} = -0{,}0014629$
$t_{in_4} = 0{,}32690172$
$t_{in_5} = 0{,}0200376$

Apply the ReLU activation function

$T_k = f(t_{in_k}) = f(0\,, t_{in_k})$
$t_1 = f(0, \quad -0{,}28235811) = 0$
$t_2 = f(0, \quad 0{,}03683466) = 0{,}03683466$
$t_3 = f(0, \quad -0{,}0014629) = 0$
$t_4 = f(0, \quad 0{,}32690172) = 0{,}32690172$
$t_5 = f(0, \quad 0{,}0200376) = 0{,}0200376$

- Calculate output in hidden layer 3

$$S_{in_m} = \sum_{k=1}^{5} t_k\, c_{km} + c_{om}$$

$$s_{in_1} = \big((0 \times (-0{,}5198651)) + (0{,}03683466 \times 0{,}65274894) + (0 \times (-0{,}71790564)) + (0{,}32690172 \times 0{,}14337844) + (0{,}0200376 \times (-0{,}10200363))\big) + 0{,}2046602 = 0{,}27353116$$

$s_{in_2} = 0{,}15381178$
$s_{in_3} = -0{,}10148221$

Apply the ReLU activation function

$S_m = f(s_{in_m}) = f(0\,, s_{in_m})$
$s_1 = f(0, \quad 0{,}27353116) = 0{,}27353116$
$s_2 = f(0, \quad 0{,}15381178) = 0{,}15381178$
$s_1 = f(0, \quad -0{,}10148221) = 0$

- Calculate output in the output layer

$$Y_{in_p} = \sum_{m=1}^{3} s_m\, b_{mp} + b_{op}$$

$$y_{in_1} = \big((0{,}27353116 \times 0{,}5020761) + (0{,}15381178 \times 0{,}51411426) + (0 \times 0{,}52120477)\big) + 0{,}45802453 = 0{,}67443482$$

$y_{in_2} = 0{,}61337965$
$y_{in_3} = 0{,}24778673$
$y_{in_4} = 0{,}01204213$
$y_{in_5} = 0{,}24388518$
$y_{in_6} = -0{,}22397366$
$y_{in_7} = -0{,}62406737$
$y_{in_8} = 0{,}07006377$
$y_{in_9} = -1{,}39301241$
$y_{in_{10}} = -0{,}98442549$
$y_{in_{11}} = -1{,}17819137$
$y_{in_{12}} = -1{,}52619137$
$y_{in_{13}} = -1{,}57035459$
$y_{in_{14}} = -1{,}67427498$

Apply the sigmoid activation function

$$Y_p = f\left(y_{in_p}\right) = \frac{1}{1 + e^{-y_{in_p}}}$$

$$y_1 = \frac{1}{1 + e^{-0{,}67443482}} = 0{,}6977859$$

$y_2 = 0{,}6772927$
$y_3 = 0{,}5315886$
$y_4 = 0{,}46700352$
$y_5 = 0{,}5501606$
$y_6 = 0{,}47381157$
$y_7 = 0{,}38135085$
$y_8 = 0{,}5283535$
$y_9 = 0{,}20921838$
$y_{10} = 0{,}25313494$
$y_{11} = 0{,}20532018$
$y_{12} = 0{,}17799029$
$y_{13} = 0{,}16453305$
$y_{14} = 0{,}16293985$

Table 4 shows the results of the feedforward calculation of the system on test data or new users. Based on the table description, the system can recommend tourist destinations to new users in the form of East Java Park 2, Selecta, East Java Park 3, East Java Park 1, and Batu City Square. Figure 9 shows the predicted output results from the feedforward calculation above with the actual output in the user's preference data. The 5 predicted outputs that have the same results as the actual output are tourist item 2 (East Java Park 2), tourist item 3 (East Java Park 3), tourist item 5 (Selecta), and tourist item 8 (Batu City Square).

Table. 4.
New User Prediction Output

Prediction output	Biner Output	Tourist Destination Items
0.6977859	1	Jatim Park 1
0.6772927	1	Jatim Park 2
0.5315886	1	Jatim Park 3
0.46700352	0	Museum Angkut
0.5501606	1	Selecta
0.47381157	0	BNS
0.38135085	0	Eco Green Park
0.5283535	1	Alun-alun Batu
0.20921838	0	Kusuma Agrotourism
0.25313494	0	Cangar
0.20532018	0	Coban Talun
0.17799029	0	Songgoriti
0.16453305	0	Coban Rais

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Prediction output	Biner Output	Tourist Destination Items
0.16293985	0	Predator Fun Park

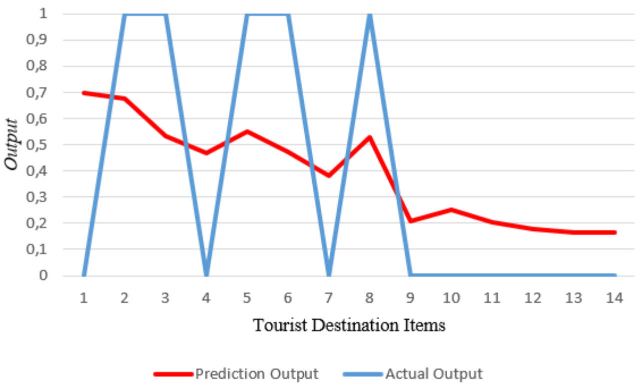

Fig. 9. Prediction output graph with actual.

In the testing phase, this study uses 20% or 46 data from the total preference data set consisting of 227 data. Moreover, calculating the system's accuracy using a confusion matrix determines the value of TP, TN, FN, and FP. Based on the results of true positive, true negative, false positive, and false negative values, accuracy, recall, precision, and f-measure can be calculated using the confusion matrix equation from 46 testing data as follows:

- $$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Precision = \frac{142}{142+123} = 0{,}5358 \times 100\% = 53{,}58\%$$

- $$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Recall = \frac{142}{142+88} = 0{,}6173 \times 100\% = 61{,}73\%$$

- $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Accuracy = \frac{142+291}{142+291+123+88} = 0{,}6723 \times 100\% = 67{,}235\%$$

- $$F-measure = \frac{2 \times Recall \times Precision}{Recall+Precision} \quad (5)$$

$$F-measure = \frac{2 \times 0{,}6173 \times 0{,}5358}{0{,}6173+0{,}5358} = \frac{0{,}66149868}{1{,}1531} = 0{,}5736 \times 100\% = 57{,}36\%$$

Based on these findings, it can be concluded that the non-rating tourist destination recommendation system used in this research can be used to provide information or data on tourist attractions to new users. Even though it got a standard accuracy score of 67.235%. However, this model can be used and developed further with various data models for further research because it produces positive values.

V. Conclusion

Based on the results above, this study discusses how to solve the problem of cold-start new users on the recommendation system. We propose a non-rating recommendation system or user preference using an artificial neural network method, a multi-layer perceptron type. This network trains user preference training data using a backpropagation learning algorithm to produce the highest training accuracy. This algorithm aims to change the weight and bias values to produce the best result. In this study, we use a network architecture of 5 – 7 – 5 – 3 – 14 from the four training data experiments due to its highest accuracy. In the input layer, there are five input variables (Profession, Hobby, Place of origin, Travel companions, Repetition), hidden layer 1 has seven neurons, hidden layer 2 has five neurons, and hidden layer 3 has three neurons, with each layer uses the ReLU activation function. There are 14 binary outputs for the output layer with a sigmoid activation function. The network architecture is used for feedforward calculations in the testing process, using the updated weights and bias values along with testing data. The output of these calculations is five recommendations for Batu City tourist destinations to new users according to their preferences. We test the system with 46 testing data from the user preference data set and calculate it using a confusion matrix resulting in an accuracy of 67.23%. The accuracy value was obtained based on the training process results from the previous four experiments, which were then used in the testing process

In this study, we only recommend tourist destinations to new users who never traveled to Batu City before and give a rating on 14 tourist destinations. For future research, the system not only solves the problem of new users but can address new items contained in the system, so that the item can be recommended to users.

References

[1] M. S. Mahfudz, Z. Arham, and E. Khudzaeva, “Development of web-based spatial information system tourism industry event distribution (case study),” *Applied Information Systems and Management (AISM)*, vol. 3, no. 2, pp. 107–112, October 2020.
[2] M. Antara and M. S. Sumarniasih, “Role of tourism in economy of bali and indonesia,” *J. Tour. Hosp. Manag.*, vol. 5, no. 2, 2017, doi: 10.15640/jthm.v5n2a4.
[3] E. Yunus and M. Indrasari, “Opportunities and challenges of tourism industry,” *Int. J. Econ. Res.*, vol. 14, no. 7, pp. 277–291, 2017.
[4] Y. D. Mahendra, “Yogyakarta tourism object recommendation system with item-based collaborative filtering approach,” Sanata Dharma, 2018.
[5] T. N. Trang Tran, M. Atas, A. Felfernig, and M. Stettinger, “An overview of recommender systems in the healthy food domain,” *J. Intell. Inf. Syst.*, vol. 50, no. 3, pp. 501–526, 2018, doi: 10.1007/s10844-017-0469-0.
[6] A. D. Putri and A. Susanto, “Hobby-based friendship recommendation system using the multicriteria decision making method,” *J. Inform. dan Rekayasa Perangkat Lunak*, vol. 2, no. 1, pp. 1–6, 2020, doi: 10.36499/jinrpl.v2i1.2787.
[7] S. Das Barman, M. Hasan, and F. Roy, “A genre-based item-item collaborative filtering: facing the cold-start problem,” *Proc. 2019 8th Int. Conf. Softw. Comput. Appl. (ICSCA ’19)*, vol. Part F1479, pp.

258–262, 2019, doi: 10.1145/3316615.3316732.

[8] A. V. Prando, F. G. Contratres, S. N. A. Souza, and L. S. De Souza, "Content-based recommender system using social networks for cold-start users," *IC3K 2017 - Proc. 9th Int. Jt. Conf. Knowl. Discov. Knowl. Eng. Knowl. Manag.*, vol. 1, no. January, pp. 181–189, 2017, doi: 10.5220/0006496301810189.

[9] B. Selva Rani and S. Ananda Kumar, "Mitigating cold start problem in a personalized recommender system," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 7, pp. 212–216, 2019.

[10] S. Sidana, M. Trofimov, O. Horodnytskyi, C. Laclau, Y. Maximov, and M. R. Amini, "User preference and embedding learning with implicit feedback for recommender systems," *Data Min. Knowl. Discov.*, vol. 35, no. 2, pp. 568–592, 2021, doi: 10.1007/s10618-020-00730-8.

[11] J. Deng, J. Guo, and Y. Wang, "A novel k-medoids clustering recommendation algorithm based on probability distribution for collaborative filtering," *Knowledge-Based Syst.*, vol. 175, pp. 96–106, 2019, doi: 10.1016/j.knosys.2019.03.009.

[12] Y. M. Arif, H. Nurhayati, F. Kurniawan, S. M. S. Nugroho, and M. Hariadi, "Blockchain-based data sharing for decentralized tourism destinations recommendation system," *Int. J. Intell. Eng. Syst.*, vol. 13, no. 6, pp. 472–486, 2020, doi: 10.22266/ijies2020.1231.42.

[13] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. E. Mohamed, and H. Arshad, "State-of-the-art in artificial neural network applications: A survey," *Heliyon*, vol. 4, no. 11, p. e00938, 2018, doi: 10.1016/j.heliyon.2018.e00938.

[14] A. Santoso and S. Hansun, "JCI prediction with backpropagation neural network," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 3, no. 2, pp. 313–318, 2019, doi: 10.29207/resti.v3i2.887.

[15] D. D. Putra, "Tourism destination recommendation system in batu city using the multi criteria recommender system method based on the 6AsTD framework," Undergraduate Thesis, UIN Maulana Malik Ibrahim Malang, 2021.

[16] O. S. Bachri, Kusnadi, M. Hatta, and O. D. Nurhayati, "Feature selection based on CHI square in artificial neural network to predict the accuracy of student study period," *Int. J. Civ. Eng. Technol.*, vol. 8, no. 8, pp. 731–739, 2017.

[17] P. Koopman, K. Driscoll, and B. Hall, "Selection of Cyclic Redundancy Code and Checksum Algorithms to Ensure Critical Data Integrity," Dot/Faa/Tc-14/49, no. March, p. 111, 2015, [Online]. Available: https://www.abbottaerospace.com/downloads/dot-faa-tc-14-49-selection-of-cyclic-redundancy-code-and-checksum-algorithms-to-ensure-critical-data-integrity/

[18] T. Wang, T. Wei, G. Gu, and W. Zou, "Checksum-aware fuzzing combined with dynamic taint analysis and symbolic execution," ACM Trans. Inf. Syst. Secur., vol. 14, no. 2, pp. 1–28, 2011, doi: 10.1145/2019599.2019600.

[19] D. J. Montana and L. Davis, "Training Feedforward Neural Networks Using Genetic Algorithms," in Proceedings of the 11th International Joint Conference on Artificial intelligence - Volume 1, 1989, vol. 89, pp. 762–767. [Online]. Available: http://dl.acm.org/citation.cfm?id=1623755.162
3876

[20] M. D. McDonnell, M. D. Tissera, T. Vladusich, A. Van Schaik, J. Tapson, and F. Schwenker, "Fast, simple and accurate handwritten digit classification by training shallow neural network classifiers with the 'Extreme learning machine' algorithm," PLoS One, vol. 10, no. 8, p. e0134254, 2015, doi: 10.1371/journal.pone.0134254.

[19] Y. Oh, S. Park, and J. C. Ye, "Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets," IEEE Trans. Med. Imaging, vol. 39, no. 8, pp. 2688–2700, 2020, doi: 10.1109/TMI.2020.2993291.

[20] Y. Oh, S. Park, and J. C. Ye, "Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets," IEEE Trans. Med. Imaging, vol. 39, no. 8, pp. 2688–2700, 2020, doi: 10.1109/TMI.2020.2993291.