JOURNAL OF APPLIED INFORMATION SYSTEMS AND INFROMATICS

Implementation of Neural Collaborative Filtering for Social Aid Recipient Recommendation

Erick Febriyanto[a], Genta Nazwar Tarempa[b], Euis Nur Fitriani Dewi[b], Muhammad Al-Husaini[b], Rifda Tri Faishal[b]

[a] *Department of Information and Computer Technology, Politeknik Negeri Subang, Subang, Indonesia*
[b] *Faculty of Engineering, Universitas Siliwangi, Tasikmalaya, Indonesia*

Corresponding author: genta.tarempa@unsil.ac.id

***Abstract*—Accurate targeting in social assistance distribution is crucial to ensure aid reaches eligible recipients and to prevent inequality or inefficiency. This study implements the Neural Collaborative Filtering (NCF) approach to recommend social assistance recipients by integrating dynamic poverty parameters. The NCF method was selected for its ability to combine Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) to capture complex non-linear relationships in multidimensional data. The dataset consists of 845 records of assistance recipients from Cijulang Village, Ciamis District, covering features such as employment, income, health, and previous assistance history. Data preprocessing includes cleaning, label encoding, one-hot encoding, and an 80:20 training–validation split. The NCF architecture employs embedding layers (dimension 32), MLP hidden layers (128–64–32 neurons), and an output layer integrating GMF and MLP components. Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Results show the model achieved an RMSE of 0.63 and MAE of 0.47 on training data, but overfitting occurred with a validation RMSE of 1.40 and MAE of 1.24. These outcomes indicate the need for hyperparameter optimization, including regularization and dropout tuning, to improve generalization. Overall, this study demonstrates NCF's potential to enhance accuracy and transparency in social assistance recommendations, promoting fairer aid distribution and reducing social jealousy through data-driven decision making. It also contributes methodologically by adapting NCF to support decision systems in the public sector..**

***Keywords*— Neural Collaborative Filtering, Recommendation System, Social Assistance, Poverty Data.**

Manuscript received 4 Oct. 2025; revised 29 Oct. 2025; accepted 13 Nov. 2025. Date of publication 13 Nov. 2025.

I. INTRODUCTION

Background study This focus on usage system recommendation in determine recipient help social in a way more accurate and efficient. In the selection process recipient help social, often happen mismatch challenges in the sector social covers giving help social by the Ministry of Social Affairs, Social Services to the Village. Poverty data Keep going increase and determination priority recipient help often difficult done with right. Therefore that, development system recommendation required for facilitate taking decision in distribution appropriate assistance. According to, usage collaborative filtering method in system recommendations on furniture stores proven effective for give recommendation suitable product to users, so that increase satisfaction users. Therefore that, development system recommendation for assistance programs social will help overcome problem in fragmented data management as well as determine priority recipient help with accurate. With apply collaborative filtering method, system recommendation This capable analyze pattern as well as preference from user [1]

Use of collaborative filtering in system recommendation can customized with preference user with high relevance to the system recommendations. For finish problem said, can take solution with development system possible recommendations give advice to the community that accepts help social.

In general, the system recommendation categorized based on the model that can applied, namely collaborative filtering, content-based filtering, and systems recommendation hybrid, [2].

Role main collaborative filtering in system processes recommendation is method most frequent filtering applied in data filtering on the system recommendations. However, the system recommendation conventional CF - based generally use approach regression that only give estimation mark without information about reliability. However, in context help social, transparency and accountability become very important. The Neural Collaborative Filtering Model, as proposed in research [3],

give solution creative with unite prediction mark as well as reliability. This model utilizes embedding layer for convert

recipient ID and criteria help, then process it via Multilayer Perceptron (MLP) to produce distribution probability every category assistance. As a result, the system No only recommend candidate recipient, but also provides a recommendation level the help that will be they accept. Therefore that, the research that will be done aiming for develop system recommendation with utilizing the neural collaborative filtering model, to increase accuracy as well as integrating dynamic parameters from changes in poverty data to in the model through the embedding layer. This is expected can overcome lack from study previously only using the collaborative filtering model or system recommendation conventional which is only give ratings to recommended objects [4].

II. METHODOLOGY

At the stage This covering data collection, data preprocessing, modeling, and deployment that can see in the illustration in figure 1.

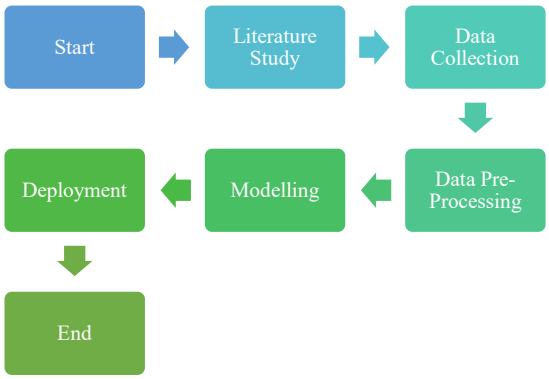

Fig. 1. Methodology Study

At the stage This gather information needed for study This source required references from various Library sources in the form of book, thesis. Journal scientific, and related articles with Neural Collaborative Filtering recommendation system, as well as implementation algorithm that is capable of implementing a recommendation system

Data Collection Techniques for get information or the facts needed in study This There is Several data collection techniques used in research This including:

A. Observation

At the stage This do observation in a way direct to field to research. Activities observation done direct for get information about help social in Cijulang Village, Observation This will focus to distribution help social as well as services available in Cijulang Village, and looking for information ongoing problems faced in giving help social in Cijulang Village

B. Follow up Survey

At the stage second from this data collection that is use Follow up survey method, follow up survey conducted about look for category addition regarding the poor for need in research, at the time after observation done, to fulfil need in do study at a time for know-how Community experience regarding distribution social assistance

At the data preprocessing stage, this is a step in building a Neural Collaborative Filtering model because data quality is very influential to Model performance. This process covers A series of techniques that can used that is.

- Data Cleaning is stages from data cleaning of lost data that can be replaced by with mean, median, mode and values cleaning from duplication of data that is not required
- Data integration combines data from various source
- Data Transformation is data transformation that can used in data preprocessing normalization with Change the Data feature Scale to the smallest 0 and 1
- Data reduction reduces amount feature or data dimension without lost information important so that analysis become more efficient
- Data splitting divides data into some sets for training, validation testing for evaluation

Following stages from preprocessing to prepare data so that the data used is quality data [5].

After do data collection and data preprocessing, then furthermore done modeling, in modeling This use Neural Collaborative Filtering method. The structure for building a Neural Collaborative Filtering model can see in illustration in figure 2 [6].

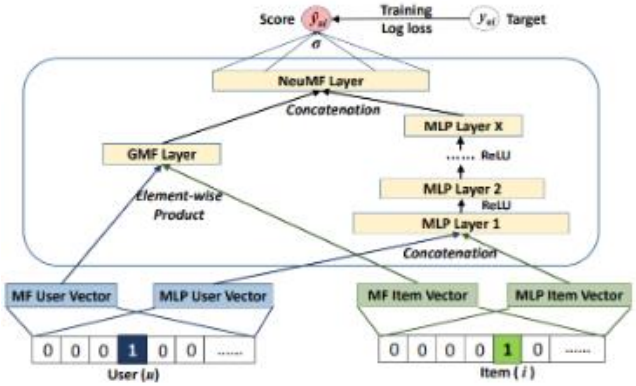

Fig. 2. NCF architecture

The input layer is part First from the usual NCF Method process consists of from User ID and Item ID implementation his as following implementation for input on the user layer and the item layer to be represented into an MF and MLP vector for users and items, more later his will become an input for GMF, and MLP [7].

At the stage furthermore after There is results representation from user and item to produce MF user vector, MLP user vector and MF item vector, MLP item vector embedding layer is used for convert categorical input user id and item id into Continuous Vector with Dimensions low.

And the purpose of this embedding layer for reduce data dimensions so that the model does not need handling big data as well as catch connection between user and item in room dimensions that more small and more efficient and increase model performance in predict user and item interactions. After the process in the Embedding Layer, where the user ID and item ID are converted become vectors continuous dimensional low (namely: MF user vector, MLP user vector, MF item vector, and MLP item vector), stages furthermore is processing interaction between vector user (user vector) with

item vector (item vector) there are objective layer interaction as following

- *Merge or bring together representation vector from users and items for catch pattern interaction they.*
- *Produce representation combination (interaction vector) that will used as input for prediction more continue [8].*

After the interaction process between vector users and items completed, results from Layer Interaction then forwarded to the Output Layer or often also known as Prediction Layer. The main purpose layer This is for produce prediction end, for example:

- Probability that user will like / interaction with an item.
- Rating value predicted by users to the item.
- Or score relevance used for determine which items are recommended [9].

III. RESULT

A. Data Collection

Research data This take from the poverty data in the village database the river as many as 900 souls whose contents like example in table 1 below.

TABLE I. INITIAL DATA ON POOR COMMUNITIES

no	nama	Kecamatan	Desa	RW	RT	No Index
1	TITIN FATIMAH	Cihaurbeuti	Cijulang	07	4	1022128
2	IIS MARLINA	Cihaurbeuti	Cijulang	03	2	1022129
3	LILIS KARMINI	Cihaurbeuti	Cijulang	03	6	1022130
4	TITIN SUMARNI	Cihaurbeuti	Cijulang	04	3	1022131

Following is example of initial data obtained from poverty data collection in Cijulang Village due to the data Not yet Enough For build a Neural Collaborative Filtering model where Neural Collaborative Filtering is the method that will be used in research This furthermore done Follow Up Survey method for obtain the necessary data for building a recommendation system with Neural Collaborative Filtering method

Follow up Survey is canal from data retrieval that has been done, which will carried out using the follow up survey method, namely complete the data of poor people with follow method activity giving benefit for poor people in the Non-Cash Assistance program, coordinate to Each RT and RW coordinates with the poor communities in their area with the Village Head in the area his.

TABLE II. FOLLOW UP SURVEY RESULTS

User_id	Name	Address	Health	Occupation	Income	item_id	Type of assistance	Help rating
1	Aah	Desa Cijulang	5	Wiraswasta	2000000	1	BPNT	5
2	Aan Dawran	Desa Cijulang	4	Buruh	1000000	2	PKH	4
3	Aan Hodijah	Desa Cijulang	2	Wiraswasta	3000000	2	PKH	4
4	Aan Safrin	Desa Cijulang	4	Wiraswasta	1500000	2	PKH	3
5	Abdul	Desa Cijulang	2	Wiraswasta	2000000	3	BPNT	2
6	Abdullah	Desa Cijulang	5	Wiraswasta	2500000	1	BPNT	4

Follow up survey results data available addition about criteria poor communities in the form of Health, Employment, Income, Item_id, Type of Assistance, and Assistance Rating and the total data that has been obtained There are 845 data on poor people.

B. Data Preprocessing

Mapping Data with Initial Dataset consists of from 900 rows about information resident along with type help the social support he receives. Each row represents One entry user -item, namely connection between residents (users) with type help certain (items). Features main in the dataset includes:

- User_id: Unique id Resident.
- Name, Address, Health, Occupation, Income: is Information demographics and population economics.
- item _id: unique id of Item
- Type of assistance: Type of assistance received
- Help_rating: Rating to help mentioned (for example from 1–5).

For make it easier processing numeric, user_id in conversion become index numeric (user_index), conversion This done with method create user_id mapping to order number start from zero, same as it is for mapping items as the result

user_id user_index
0 1022726 0
1 1022590 1
item_id item_index
0 1 0
1 1 0
2 3 1

Amount user unique in the dataset is 900, so that index maximum used is 899. This step is very important Because Lots machine learning algorithms work better and faster with representation numeric simple like index than text ID or numeric random. This process helps simplify representation of items in the model and maintaining data format consistency.

A number of feature categorical such as Name, Address, and Occupation No can direct processed by machine learning algorithms because shaped text. Therefore that, Label Encoding is done, namely technique change string value becomes number round

Setelah Label Encoding User Features:

	Nama_encoded	Alamat_encoded	Pekerjaan_encoded
0	0	0	6
1	0	0	6
2	0	0	1
3	1	0	3
4	2	0	3

Fig. 3. User Label Encoding Results

Setelah Label Encoding Item Features:

	Nama_encoded	Alamat_encoded	Pekerjaan_encoded	Jenis_Bantuan_encoded
0	0	0	6	2
1	0	0	6	2
2	0	0	1	1
3	1	0	3	0
4	2	0	3	0

Fig. 4. Item Label Encoding Results

Every category given number unique. For example, " Self Employed " might get code 6, while "IRT" gets code 2, and so on. Label Encoding allows the model to reading and processing categorical data without remove information semantics.

Although Label Encoding has been converting text to numbers, there are possibility that the model will wrong conclude that category with number more tall own mark bigger. For prevent problem in this case, One-Hot Encoding is applied to the feature category such as Name, Address, and Occupation. The output of one-hot encoding is making column addition for every category, which has a value of 0 or 1 (binary). Sure! Go ahead. give the text you want to paraphrase.

Setelah One-Hot Encoding User Features:

	user_id	user_index	user_Nama_0	user_Nama_1	user_Nama_2	user_Nama_3	\
0	1022726	0	1.0	0.0	0.0	0.0	
1	1022590	1	1.0	0.0	0.0	0.0	
2	1022626	2	1.0	0.0	0.0	0.0	
3	1022677	3	0.0	1.0	0.0	0.0	
4	1022823	4	0.0	0.0	1.0	0.0	

	user_Nama_4	user_Nama_5	user_Nama_6	user_Nama_7	...	user_Nama_758	\
0	0.0	0.0	0.0	0.0	...	0.0	
1	0.0	0.0	0.0	0.0	...	0.0	
2	0.0	0.0	0.0	0.0	...	0.0	
3	0.0	0.0	0.0	0.0	...	0.0	
4	0.0	0.0	0.0	0.0	...	0.0	

	user_Alamat_0	user_Pekerjaan_0	user_Pekerjaan_1	user_Pekerjaan_2	\
0	1.0	0.0	0.0	0.0	
1	1.0	0.0	0.0	0.0	
2	1.0	0.0	1.0	0.0	
3	1.0	0.0	0.0	0.0	
4	1.0	0.0	0.0	0.0	

	user_Pekerjaan_3	user_Pekerjaan_4	user_Pekerjaan_5	user_Pekerjaan_6	\
0	0.0	0.0	0.0	1.0	
1	0.0	0.0	0.0	1.0	
2	0.0	0.0	0.0	0.0	
3	1.0	0.0	0.0	0.0	

Fig. 5. One Hot Encoding user results

Setelah Label Encoding Item Features:

	Nama_encoded	Alamat_encoded	Pekerjaan_encoded	Jenis_Bantuan_encoded
0	0	0	6	2
1	0	0	6	2
2	0	0	1	1
3	1	0	3	0
4	2	0	3	0

Setelah One-Hot Encoding Item Features:

	item_id	item_index	item_Jenis_Bantuan_0	item_Jenis_Bantuan_1	\
0	1	0	0.0	0.0	
1	1	0	0.0	0.0	
2	3	1	0.0	1.0	
3	2	2	1.0	0.0	
4	2	2	1.0	0.0	

	item_Jenis_Bantuan_2
0	1.0
1	1.0
2	0.0
3	0.0
4	0.0

Fig. 6. One Hot Encoding Item Results

After do one hot encoding stage, label encoding and data mapping, then perform data splitting for divide the data into train data and validation data.

```
Training users shape: (676,)
Training items shape: (676,)
Training targets shape: (676,)
Validation users shape: (169,)
Validation items shape: (169,)
Validation targets shape: (169,)
```

Fig. 7. Split Data Results

C. Modeling

1) NCF Model

After perform further data preprocessing Neural Collaborative filtering model creation This model creation done on google collab results from modeling his Can seen in figure 8 below:

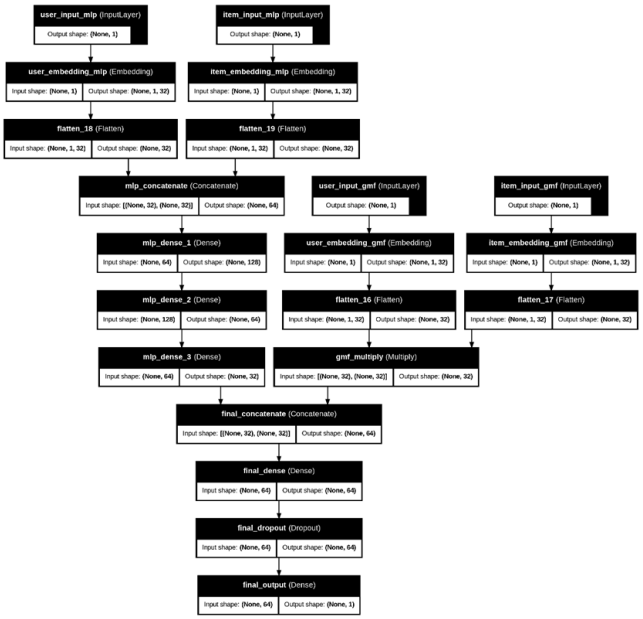

Fig. 8. NCF Model Results

This NCF model user_input_mlp and item_input_ mlp: Input layer for receive user ID (community) and item ID

(help) social). Output shape (None, 1). Next enter to Embedding layer user_embedding_mlp and item_embedding_ mlp: Embedding layer for convert user ID and item ID to vector continuous with dimensions low (32-dimensional). Output shape (None, 1, 32). Continue entering into the Interaction of flatten_2 and flatten_ 3 layers: This layer changes the output embedding form from (None, 1, 32) to (None, 32).

mlp_concatenate: Merge user and item embedding vectors become One vector with form (None, 64).

mlp_dense_1, mlp_dense_2, mlp_dense_3: A series of Dense layers for processing vector combination:

mlp_dense_1: Input (None, 64) → Output (None, 128)

mlp_dense_2: Input (None, 128) → Output (None, 64)

mlp_dense_3: Input (None, 64) → Output (None, 32)

user_embedding_gmf and item_embedding_gmf:

Embedding layer for GMF branch.

gmf_multiply: Do multiplication element by element between user and item embedding vectors, generating vector with form (None, 32).

final_dense: Dense Layer for processing vector combination from GMF and MLP branches, resulting in vector with form (None, 64).

final_dropout: Layer Dropout for prevent overfitting

final_output: Last Dense Layer For produce prediction end with form (None, 1).

In the embedding layer the total parameters generated user_embedding_mlp: 27,040 parameters (count unique user × embedding dimension = 845 × 32) and for its items 96 parameters (number of unique items × embedding dimension = 3 × 32), MLP Branch with Dense layer activation produces the first Dense Layer with 128 units, resulting in vector with shape (None,128). Parameters: 64×128+128=8,320, Second Dense Layer with 64 units, resulting in vector with shape (None,64). Parameters: 128×64+64=8,256. The third Dense layer with 32 units, resulting in vector with shape (None,32). Parameters: 64×32+32=2,080. Last Dense layer before dropout, resulting in vector with shape (None,64). Parameters: 64×64+64=4,160, last Dense Layer For produce prediction end with form (None, 1). Parameters: 64×1+1=65, so the total feasible parameters tested on this NCF model A total of 77,153 were trainable.

2) Model Evaluation.

After formed the structure of this NCF model furthermore testing and evaluation on the NCF Model, the testing carried out use RMSE and MAE methods, in model testing have 4 inputs for testing among them, gmf_input (user, item) and mlp_input (user, item).

Epoch	Loss	MAE	RMSE	Val_Loss	Val_MAE	Val_RMSE
1	1.3231	0.5743	0.7602	2.8715	1.2724	1.4687
5	1.0142	0.4759	0.6373	2.7165	1.2628	1.4590
10	0.9376	0.4855	0.6534	2.6950	1.2866	1.4817
13	0.8901	0.4728	0.6473	2.4312	1.1845	1.4017
17	0.8310	0.4687	0.6332	2.4889	1.2365	1.4355
18	0.8704	0.4937	0.6655	2.6526	1.3004	1.4959

Fig. 9. Test Results Table

In the table results evaluation show testing with using MAE and RMSE with amount testing 20 Epoch shows that Loss value: Loss value on training data decrease in a way significant from 1.3231 (Epoch 1) to 0.8310 (Epoch 17), indicating that the model is increasingly Good in minimize error prediction during training. Val_Loss: Validation loss value still high and fluctuating, starting from 2.8715 (Epoch 1) and only down to 2.4889 (Epoch 17). This is showing potential for overfitting, where the model is too specific studying training data and less capable generalize new data.

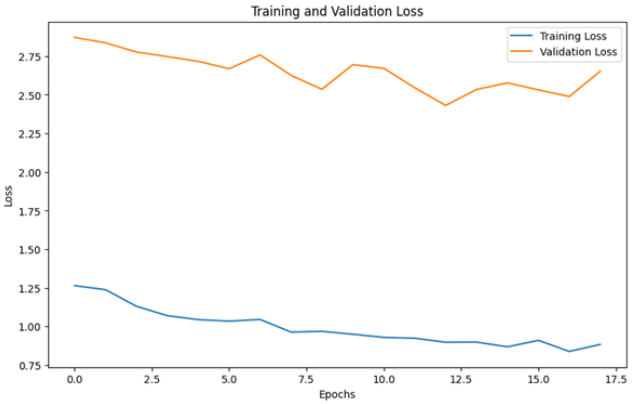

Fig. 10. Training and Validation Loss

And evaluation using MAE and RMSE with MAE (Mean Absolute Error) value: MAE decreases from 0.5743 to 0.4687, indicating improvement accuracy prediction with reduction error absolute average of ~18%. Val_Loss: Validation loss value still high and fluctuating, starting from 2.8715 (Epoch 1) and only down to 2.4889 (Epoch 17). This is showing potential for overfitting, where the model is too specific studying training data and less capable generalize new data.

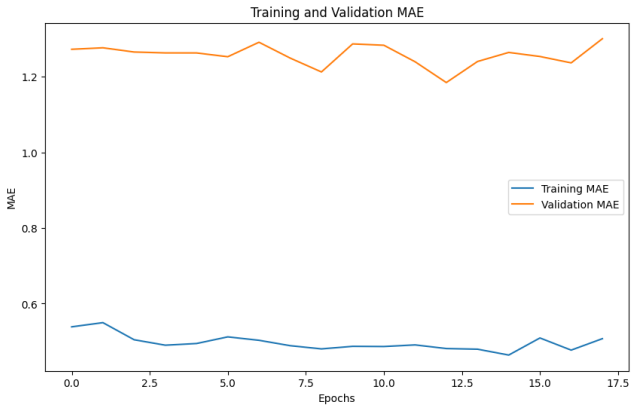

Fig. 11. MAE Training and Validation

Val_MAE and RMSE (Root Mean Square Error): RMSE goes down from 0.7602 to 0.6332, indicating that variation error predictions are also increasing decreased. Val_RMSE: Both metric validation No show trend consistent decline. For example, Val_MAE at Epoch 9 reached 1.2125, however increase return to 1.3004 in Epoch 18. Val_RMSE also fluctuates around 1.42–1.49, indicating instability prediction on validation data.

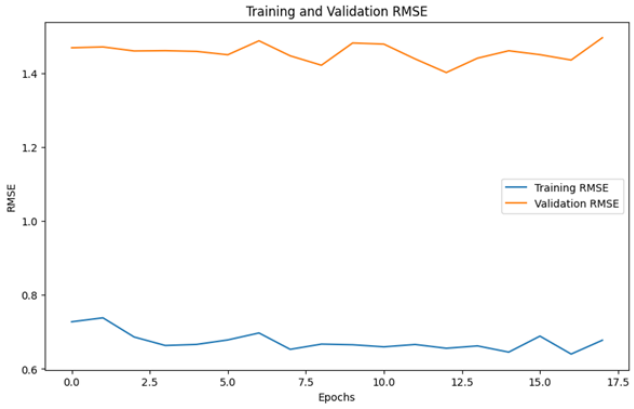

Fig. 12. Training and Validation RMSE

Implementation System Recommendation For help social is stages that aim for give recommendation appropriate assistance with designing the model that has been made, after training on the NCF model deployment of the Neural Collaborative Filtering model which has been designed will made into a web information with using the Streamlit framework with the web name " SIREKOM-BS" system recommendation help social.

Fig. 13. Home Page

On the page home page This will display information distribution from residents who have ever get help social Can seen in figure 14 regarding distribution type assistance available in the Cijulang Village Community.

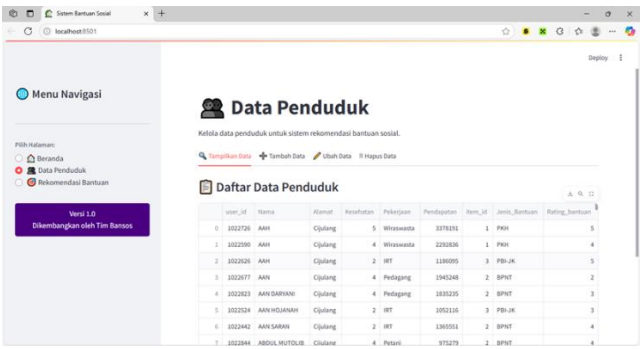

Fig. 14. Population Data Page

On the Population Data menu This give information about Who only that has been get help social, as for the uses from the population data menu This is so that residents who have accept help No can accept help others. so that the problem jealousy social between communities can reduced, and in the population data menu Can add population, edit population, and remove resident.

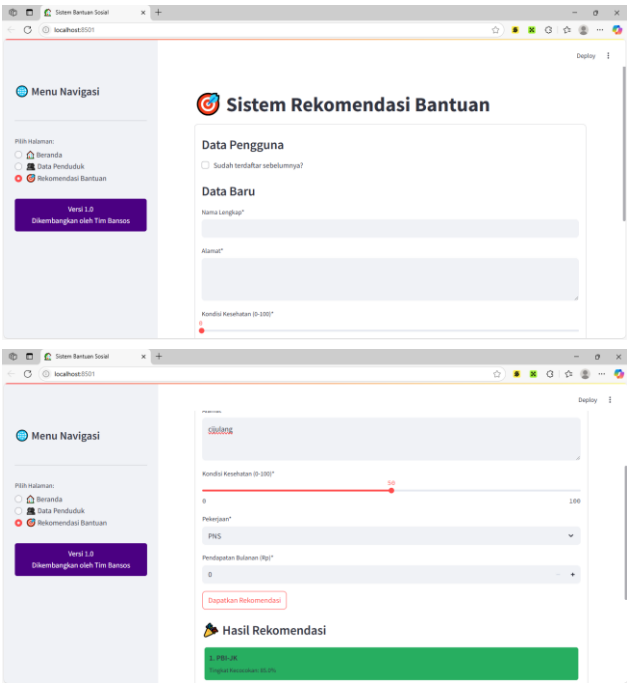

Fig. 15. Population Recommendation Page

On the Recommendation Menu Page aiming for give recommendation help to the Community in submission help to village cijulang which will be later his will get relevant recommendations with his condition.

IV. Conclusion

Based on results research and development system recommendation recipient help social use Neural Collaborative Filtering (NCF) method, can take a number of conclusions as following:

The NCF model is successful produce prediction recommendation help social based on demographic data and preferences society. With utilizing embedding layers, this model capable represent characteristics society and types help in form vector numeric which then processed through Multilayer Perceptron (MLP) and Generalized Matrix Factorization (GMF) architectures.

Evaluation results show that the model is capable produce prediction with RMSE value of 0.6332 and MAE of 0.4687 at the 17th epoch. Although there are fluctuations in the validation data that indicate potential overfitting, model performance on training data shows positive trend.

With existence embedding representation, the model can catch change poverty data pattern in a way more responsive. This is helping Cijulang Village in determine priority recipient help in a way more objective and transparent.

After the model is trained and evaluated, the system realized in form web application. Application This make it easier officer village and also service social in:

- Enter candidate data recipient help.
- View the list of recommendations help social.
- Tracking history reception help.

Different with researches previously focused on the business domain or entertainment (such as movie recommendations or product), research This try applying NCF to context social, namely in the aid program social. The results show that approach This worthy developed more carry on.

REFERENCES

[1] TIRUAN MULTI-LAYER PERCEPTRON UNTUK PREDIKSI PENYINARAN MATAHARI KOTA BANDUNG. KOMPUTA : Jurnal Ilmiah Komputer Dan Informatika, 12(1).

[2] Bobadilla, J., Gutiérrez, A., Alonso, S., & González-Prieto, Á. (n.d.). Neural Collaborative Filtering Classification Model to Obtain Prediction Reliabilities.

[3] Chen, H., Shi, S., Li, Y., & Zhang, Y. (2021). Neural collaborative reasoning. The Web Conference 2021 - Proceedings of the World Wide Web Conference, WWW 2021, 1516–1527. https://doi.org/10.1145/3442381.3449973

[4] Dzumiroh, L. (2012). (n.d.). PENERAPAN METODE COLLABORATIVE FILTERING.

[5] Februariyanti, H., Dwi Laksono, A., Sasongko Wibowo, J., & Siswo Utomo, M. (2021). IMPLEMENTASI METODE COLLABORATIVE FILTERING UNTUK SISTEM REKOMENDASI PENJUALAN PADA TOKO MEBEL. www.unisbank.ac.id

[6] Fkih, F. (2021). Similarity measures for Collaborative Filtering-based Recommender Systems: Review and experimental comparison. In Journal of King Saud University - Computer and Information Sciences. King Saud bin Abdulaziz University. https://doi.org/10.1016/j.jksuci.2021.09.014

[7] Fkih, F. (2021). Similarity measures for Collaborative Filtering-based Recommender Systems: Review and experimental comparison. In Journal of King Saud University - Computer and Information Sciences. King Saud bin Abdulaziz University. https://doi.org/10.1016/j.jksuci.2021.09.014

[8] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017). Neural collaborative filtering. 26th International World Wide Web Conference, WWW 2017, 173–182. https://doi.org/10.1145/3038912.3052569

[9] Irfan, M., Dwi C, A., & Fika, H. R. (n.d.). METODE COLLABORATIVE FILTERING.

[10] Nugroho, D. A., Lubis, C., & Perdana, N. J. (2024). SISTEM REKOMENDASI FILM MENGGUNAKAN METODE NEURAL COLLABORATIVE FILTERING MOVIE RECOMMENDATION SYSTEM USING NEURAL COLLABORATIVE FILTERING. Journal of Information Technology and Computer Science (INTECOMS), 7(3).

[11] Pamuji, A. (n.d.). SISTEM REKOMENDASI KREDIT PERUMAHAN RAKYAT DENGAN MENGGUNAKAN METODE COLLABORATIVE FILTERING.

[12] Rahmawati, S., Nurjanah, D., & Rismala, R. (2018). Analisis dan Implementasi pendekatan Hybrid untuk Sistem Rekomendasi Pekerjaan dengan Metode Knowledge Based dan Collaborative Filtering. Indonesian Journal on Computing (Indo-JC), 3(2), 11. https://doi.org/10.21108/indojc.2018.3.2.210

[13] Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2009). *BPR: Bayesian personalized ranking from implicit feedback*. Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence, 452–461.

[14] Koren, Y., Bell, R., & Volinsky, C. (2009). *Matrix factorization techniques for recommender systems*. Computer, 42(8), 30–37. https://doi.org/10.1109/MC.2009.263

[15] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). *Deep learning based recommender system: A survey and new perspectives*. ACM Computing Surveys (CSUR), 52(1), 1–38. https://doi.org/10.1145/3285029

[16] Sedhain, S., Menon, A. K., Sanner, S., & Xie, L. (2015). *AutoRec: Autoencoders Meet Collaborative Filtering*. In Proceedings of the 24th International Conference on World Wide Web, 111–112.

[17] Wang, H., Wang, N., & Yeung, D. Y. (2015). *Collaborative deep learning for recommender systems*. Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1235–1244. https://doi.org/10.1145/2783258.2783273

[18] Adomavicius, G., & Tuzhilin, A. (2005). *Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions*. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

[19] Ricci, F., Rokach, L., & Shapira, B. (2015). *Recommender Systems Handbook*. Springer. https://doi.org/10.1007/978-1-4899-7637-6

[20] Gunawan, D., & Basuki, R. (2020). *Penerapan Neural Collaborative Filtering pada Sistem Rekomendasi Buku Berbasis Web*. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 4(3), 524–531. https://doi.org/10.29207/resti.v4i3.1987

[21] Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). *Item-based collaborative filtering recommendation algorithms*. Proceedings of the 10th International Conference on World Wide Web, 285–295.

[22] Schafer, J. B., Konstan, J., & Riedl, J. (2001). *E-commerce recommendation applications*. Data Mining and Knowledge Discovery, 5, 115–153.

[23] Alfarizi, M. A., & Wibowo, A. (2022). *Sistem Rekomendasi Penyaluran Bantuan Sosial Menggunakan Metode Hybrid Filtering*. Jurnal Ilmiah Teknologi dan Rekayasa, 17(2), 33–41.

[24] Putra, R. H., & Nasution, R. A. (2021). *Rancang Bangun Sistem Rekomendasi Penerima Bantuan Sosial Berbasis Machine Learning*. Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK), 8(4), 599–606. https://doi.org/10.25126/jtiik.202184534

[25] Widodo, A. R., & Prasetyo, E. (2023). *Penggunaan Algoritma Deep Learning pada Sistem Rekomendasi untuk Program Bantuan Pemerintah*. Jurnal Sistem Informasi dan Komputerisasi Akuntansi (JSIKA), 12(1), 20–28.