A Deep Learning Framework for Personalized Land Parcel Recommendation: Integrating TF-IDF User Profiling with Spatial Analytics

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Abstract
Selecting land parcels for purchase or development requires the evaluation of multiple spatial, economic, and user-specific factors. Existing recommender systems in property and spatial decision-support domains commonly rely on collaborative filtering or conventional content-based approaches. However, these methods are often limited in land administration contexts, where transaction records are sparse, parcel characteristics are heterogeneous, and user preferences are context-dependent. To address this limitation, this study proposes an AI-driven land parcel recommendation framework based on a Feature-based Multi-Criteria Recommendation System (FMCRS), integrating user-profile information with spatial and economic land attributes. User identity and professional affiliation were transformed into numerical features using Term Frequency–Inverse Document Frequency (TF-IDF), while land attributes included road width, zoning classification, distance to the central business district (CBD), and predicted land value. The framework was evaluated using data from land valuation professionals in Surabaya City by comparing Ordinary Least Squares (OLS) and Deep Neural Network (DNN) models. The DNN model achieved better predictive performance than OLS, with an R^2 of 0.92 and a MAPE of 4% on the training dataset, as well as slightly higher testing performance. These results indicate that the proposed framework can better capture non-linear relationships between user profiles and spatial land attributes. Overall, this approach is relevant for supporting personalized, spatially informed, and data-driven land parcel recommendation in complex urban environments with limited historical interaction data.

Keywords: Deep Neural Network, Ordinary Least Squares, Land Parcel, Recommendation System

1. Introduction

The proliferation of geospatial data has facilitated the widespread adoption of recommendation systems in both commercial and academic domains. Traditionally, identifying suitable land parcels is a labour-intensive process reliant on manual searching, expert judgment, and the simultaneous evaluation of complex spatial and economic constraints. As the volume and heterogeneity of spatial data expand, manual selection becomes increasingly inefficient. Recent developments in recommendation systems have demonstrated their capability to support multi-criteria decision-making processes by identifying items that align with user preferences and contextual requirements [1] and [2]. In spatial decision-support environments, recommendation systems are increasingly integrated with geospatial visualization and analytical platforms to improve contextual interpretation and support informed decision-making [3] and [4]. Recent studies have also highlighted the increasing integration of Artificial Intelligence (AI) and spatial data analytics in urban and spatial decision-support systems, particularly for handling large-scale heterogeneous geospatial datasets [5].

Central to the architecture of recommendation engines lies the assumption that meaningful relationships exist between users and items. By considering historical interaction data, these systems aim to infer user interests and predict future preferences, as past behaviour often serves as a reliable indicator of subsequent choices [6]. Among the most widely adopted recommendation approaches is Content-Based Filtering (CBF), a

foundational approach, generates recommendations by matching item attributes with user profiles. Despite its high interpretability, this method has inherent limitations. It tends to reinforce established user preferences, thus creating a "filter bubble" and relies heavily on the availability of detailed user profile data, limiting its utility in scenarios involving new users or items with sparse descriptive data [7]. In contrast, Collaborative Filtering (CF) prioritizes collective user behaviour over individual item attributes [8]. This approach constructs a preference matrix from user–item interactions to identify similarity patterns. Consequently, users may discover items they have not previously encountered, based on the preferences of peer groups with similar behaviours. CF has been widely applied in domains where item attributes are ill-defined or where user preferences are subjective, such as e-commerce and tourism applications [9].

CF techniques are generally categorized into item-based and user-based approaches. Item-based filtering identifies similarities among items based on user interaction histories, whereas user-based filtering focuses on similarities among users to predict preferences [9] and [10]. Although both approaches follow similar computational steps, their performance is contingent on data density. Item-based methods often struggle when interaction data is sparse, as limited co-occurrence leads to unreliable similarity calculations. Conversely, user-based filtering offers greater flexibility in capturing relationships among users and remains effective even when detailed item information is limited [11].

While CF has proven effective in high-frequency domains like online retail [12] [13] and [14], its reliance on dense historical data poses significant challenges in the property sector. Furthermore, CF requires overlapping user interactions on identical items to extract preference similarities [15]. In real estate, where transactions are infrequent and high-value, CF frequently encounters the "cold start" problem, failing to provide meaningful recommendations to new users due to insufficient historical data [16]. In land administration contexts, land parcel suitability is inherently a multi-criteria problem involving zoning regulations, accessibility, legal status, physical characteristics, surrounding land use, and economic considerations. Consequently, recent studies have increasingly explored Feature-based Multi-Criteria Recommendation Systems (FMCRS) as an alternative framework for spatial and land-related recommendation problems. Unlike conventional CF approaches, FMCRS utilizes explicit attributes of both users and items, enabling recommendations to be generated even when historical interaction data are limited. This characteristic makes FMCRS particularly relevant for land administration and cadastral contexts, where transactions are relatively infrequent and parcel characteristics are highly heterogeneous [17]. Recent studies have also begun exploring recommendation-oriented approaches within cadastral and land administration systems, indicating the growing relevance of intelligent recommendation frameworks in land-related services [18].

However, a primary challenge in implementing FMCRS lies in the model's ability to accurately capture the complex interactions between user and item characteristics [19]. The relationship between a user's profile and the suitability of a land parcel is rarely linear [20]. In property and housing market analysis, traditional linear or hedonic regression models may also neglect non-linear interactions among explanatory variables, which can limit their predictive performance in complex valuation contexts [21]. Information asymmetry and the heterogeneity of land characteristics further complicate the prediction of accurate ratings [22]. Artificial Intelligence (AI) algorithms have demonstrated the capacity to model complex, non-linear relationships between feature contexts and target labels [23]; yet, the exploration of AI-driven algorithms for land parcel recommendation remains limited.

This study addresses this gap by proposing an AI-based land parcel recommendation framework utilizing an FMCRS approach. The need for such a framework arises from the specific characteristics of land administration, where user–parcel interaction data are limited, land transactions are infrequent, and parcel suitability depends on complex combinations of spatial, economic, regulatory, and user-specific factors. The proposed framework integrates explicit user preference information with spatial and economic land attributes to predict personalized ratings. To evaluate the necessity of complex modelling, this study compares two algorithms with different modelling assumptions: Ordinary Least Squares (OLS) and Deep Neural Network (DNN). OLS is employed as a transparent linear baseline to assess whether user preferences can be explained through simple linear relationships, whereas DNN is selected because deep learning-based recommender models have been shown to capture non-trivial, non-linear, and hidden relationships between users and items in multi-criteria recommendation settings [22]. This comparison provides empirical insight into whether AI-based non-linear modelling offers added value beyond a conventional linear approach.

The proposed framework is evaluated through a case study in Surabaya City by generating spatial visualizations of predicted ratings and ranked land parcel recommendations. Through this approach, the study contributes to the development of personalized, spatially informed, and data-driven decision-support systems for land valuation and land parcel selection.

2. Research Methodology

This study was conducted in Surabaya City, Indonesia, a rapidly developing urban centre characterized by diverse land use patterns and fluctuating land values. As one of Indonesia's primary metropolitan areas, Surabaya exhibits significant spatial heterogeneity driven by varying zoning regulations, infrastructure accessibility, and proximity to the Central Business District (CBD). These dynamic urban characteristics render Surabaya a suitable case study for evaluating a land parcel recommendation framework that aims to integrate complex spatial attributes with individual user preferences. Figure 1 illustrates the architecture of the proposed Feature-based Multi-Criteria Recommendation System (FMCRS). The framework is designed to synthesize user interaction data with spatial land attributes to generate personalized recommendations. The workflow initiates at the User Interface module, which facilitates user authentication, profile creation, and the collection of explicit preference ratings. Users evaluate specific land parcels on a 5-point Likert scale, where a rating of 5 indicates maximum preference. These interactions are stored in a dedicated User Database containing User IDs, profile vectors, and historical ratings. Simultaneously, the system queries the Land Parcel Database to retrieve spatial characteristics corresponding to the rated Parcel IDs. Key attributes include road width, zoning classification, Euclidean distance to the Central Business District (CBD), and predicted land value. The selection of these variables is grounded in prior literature, which identifies accessibility, zoning, and infrastructure as critical determinants of property value. Notably, the land value attribute is derived from pre-calculated valuation models specific to Surabaya City [20]. In the final stage, the Recommendation Engine integrates these spatial attributes with user profile features. This combined dataset serves as the input for the predictive models, which are trained to infer user ratings for unvisited parcels. The system subsequently ranks these predictions to generate a list of personalized land parcel recommendations. Figure 2 illustrates the prototype user interface utilized as a data collection tool for the recommendation engine. The interface displays a visualization of land values based on specific classifications. Users can interact with the map using various basemaps, such as OpenStreetMap (OSM), ESRI World Imagery, and CartoDB to adjust the visual context. A key feature of the system is the interactive pop-up window triggered upon parcel selection, which displays essential attributes such as land value, zoning, road width, and location descriptions. Currently, this prototype serves primarily as a medium for collecting user ratings and associated land characteristics. User profile information is captured via a separate electronic form and subsequently integrated with the rating data during the processing stage.

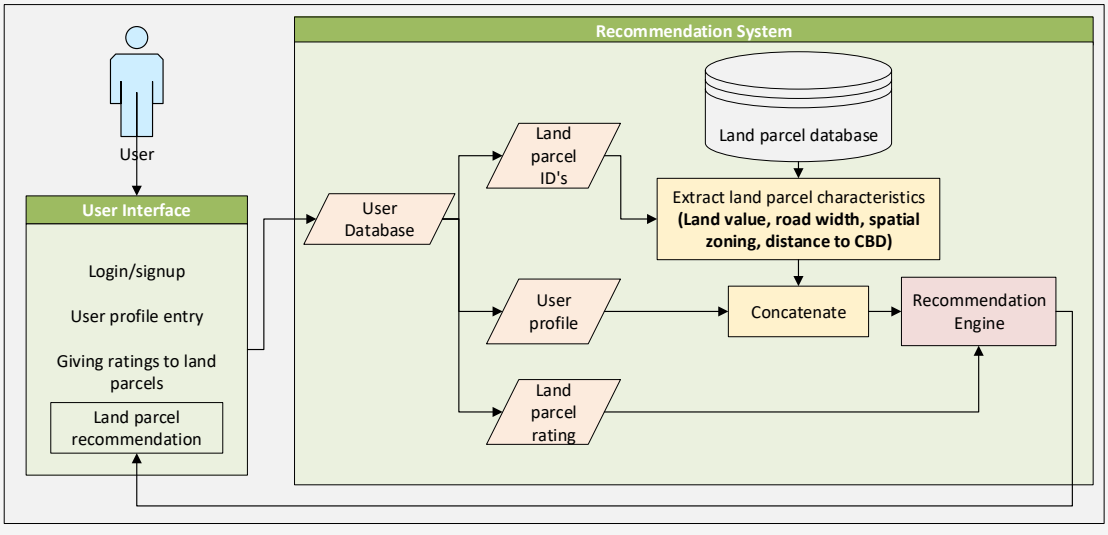


Figure 1: Proposed architecture of recommendation systems

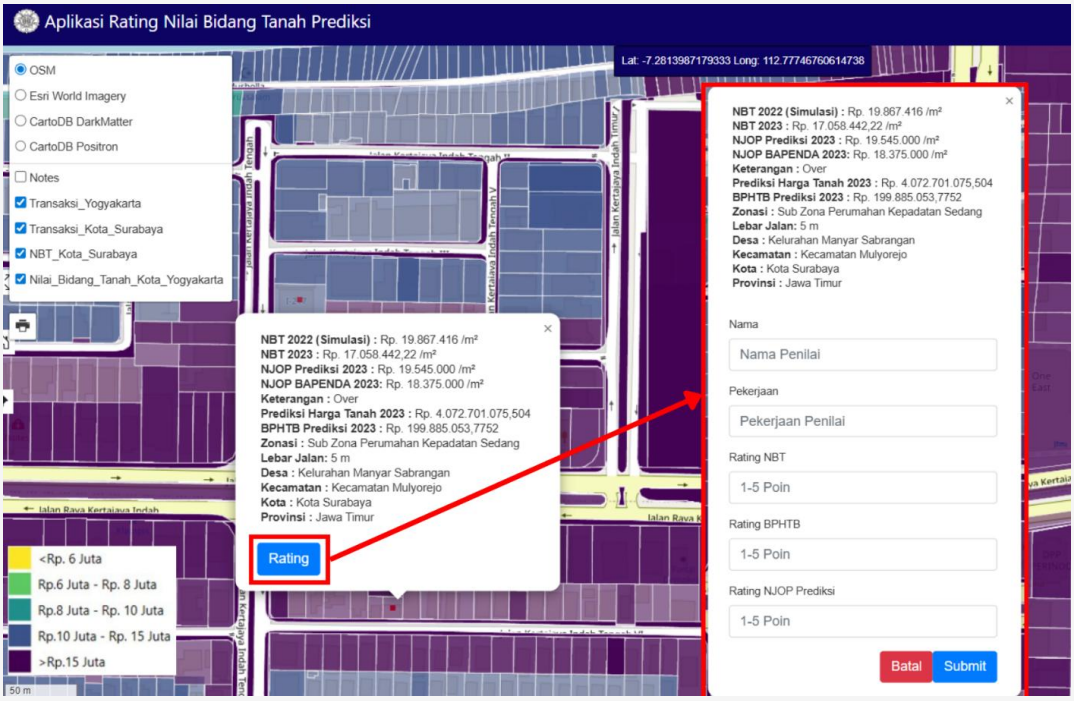


Figure 2: Prototype user interface for rating data retrieval

As this research focuses on framework development, the system components were not fully integrated in real-time. The interface functioned solely for data acquisition. This modular, unintegrated approach facilitates independent testing, ensuring that the evaluation of the rating module remains unaffected by potential modifications to the recommendation engine. The dataset for recommendation system modelling was derived from primary data collection, involving the deployment of the interface prototype to a targeted group of land assessment professionals. The participants included real estate appraisers, land surveyors, urban planners, government officials, and other practitioners involved in land administration. This purposive selection ensured that the collected ratings reflected informed professional judgments rather than general public preferences.

Each participant was assigned a unique User ID, and their professional affiliation was recorded in textual form. Participants evaluated land parcels via the web-based survey interface depicted in Figure 2. Ratings were submitted using a five-point Likert scale, where a score of 1 represents the lowest preference and a score of 5 represents the highest. The five-point scale was selected because it provides a balance between simplicity and sufficient response variation, while reducing respondent burden. Compared with broader rating scales, such as a nine-point scale, a five-point scale is generally easier for respondents to understand and may improve response consistency and data quality [32] and [33]. Dataset for recommendation system modelling was obtained primarily, implying that the interface prototype was implemented for several users affiliated with land assessment. These user affiliations include real estate appraisers, land surveyors, urban planners, government officials, and other practitioners involved in land administration. This selection was intended to ensure that the collected ratings reflect informed assessments rather than general public preferences. Each user was assigned a unique User ID, and affiliation information was recorded in textual form. Users were asked to evaluate land parcels through a web-based survey interface, as shown in Figure 2. Users provided ratings using a five-point Likert scale, where a score of 1 represents the lowest preference and a score of 5 represents the highest. This scale was selected to balance simplicity and descriptive capability while reducing respondent burden and maintaining data reliability. The spatial distribution of user ratings across the study area is illustrated in Figure 3(a), where point size correlates with rating magnitude and distinct colours differentiate individual users. To protect respondent privacy, personal names, contact information, and direct identifiers were removed from the modelling dataset. Each respondent was represented using a pseudonymized User ID, which was used only for modelling purposes. Given the small number of professional respondents, detailed respondent-linked rating records were not publicly disclosed, and any

future data sharing should generalize affiliation information into broader occupational categories to reduce potential re-identification risks.

The list of users and their affiliations, along with the TF-IDF transformation results for the affiliations, is presented in Table 1. Table 1 shows that several affiliations, including "Department of Public Housing and Residential Areas and Land Affairs" (TF-IDF = 2.809) and "Surabaya Regional Financial and Asset Management Agency" (TF-IDF = 2.635), have the highest TF-IDF scores. These values indicate that the corresponding affiliation terms are relatively more distinctive within the corpus of user affiliations. Conversely, affiliations such as "Notary/PPAT" (TF-IDF = 1.414) and "National Land Agency Surabaya Office 1" (TF-IDF = 1.392) have lower scores, suggesting that their textual terms are either more common across the affiliation corpus or less distinctive. The scalar TF-IDF affiliation scores served as input features for the predictive models to represent users' professional affiliations in numerical form. This scalar representation was used instead of the full TF-IDF vector to reduce feature dimensionality, considering the limited number of rating observations. The incorporation of these scores enabled the models to c(a)der variation in users' professional backgrounds. User ID, land parcel attributes, and TF-IDF affiliation scores were then processed as modelling parameters in both the OLS and DNN approaches. The characteristics of the land parcels are shown in Figure 3(b).

The dataset used for model training consisted of 202 rating observations collected from 19 users. Meanwhile, the complete candidate land parcel database contained 713,764 parcels, which were used during the model implementation stage to generate predicted ratings and Top-10 recommendations. Based on the number of observed user–parcel ratings relative to all possible user–parcel combinations, the dataset sparsity level was approximately 0.999, indicating a highly sparse dataset. Therefore, this study evaluates the effectiveness of an FMCRS framework integrated with AI algorithms for generating land parcel recommendations under very sparse rating data conditions. Data processing methods in the recommendation engine proposed in this study are shown in Figure 4. There are four main processes in this study, namely pre-processing, modelling, model evaluation, and model implementation. The first stage is data pre-processing, which aims to standardize the format and dimensions of the input data. Since the modelling process requires numerical input, character-based variables such as User ID and pro(b)onal affiliation were transformed into numerical representations.

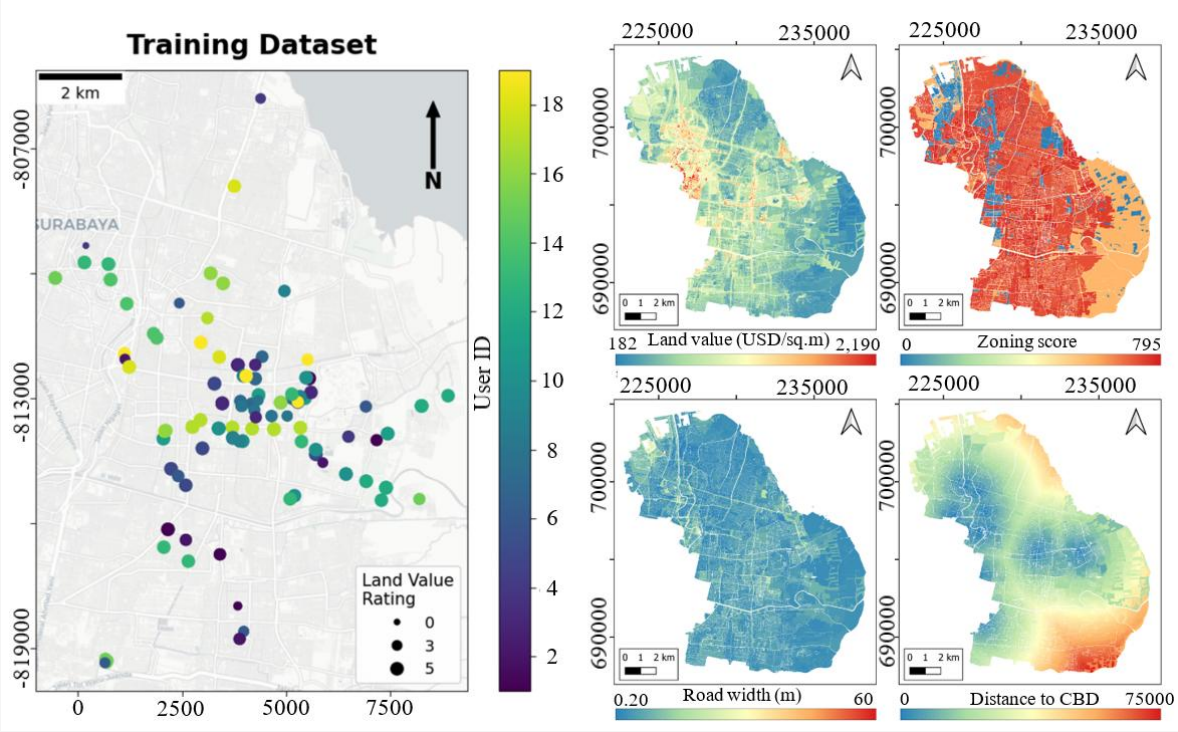


Figure 3: Dataset for the MCRS prediction model training process

Table 1: Users' affiliation TF IDF

User ID	Affiliation	TF IDF
1	Assessor from KJPP SISCO	1.732
2	National Land Agency Office 2 Land Acquisition	1.966
3	Non-Civil Servant National Land Agency Surabaya Office 1	1.645
4	National Land Agency Regional Office Jawa Timur - Land Technical Considerations (PTP)	2.174
5	Surabaya Regional Financial and Asset Management Agency	2.635
6	National Land Agency Regional Office Jawa Timur - Prosecution and Investigation (P2)	2.174
7	Employee - National Land Agency Surabaya Office 1	1.940
8	Employee - National Land Agency Surabaya Office 1	1.940
9	National Land Agency Surabaya Office 1	1.392
10	Department of Public Housing and Residential Areas and Land Affairs	2.809
11	National Land Agency Office 1	1.924
12	Surabaya Regional Financial and Asset Management Agency	2.635
13	National Land Agency Office 2 Land Acquisition	1.966
14	Surabaya Regional Financial and Asset Management Agency	2.635
15	National Land Agency Regional Office Jawa Timur - Dispute Control and Handling (PPS)	2.174
16	National Land Agency Office 2 Land Acquisition	1.966
17	Civil Servants in the Government and Public Welfare Section	2.428
18	National Land Agency Office 2 Land Acquisition	1.966
19	Notary/Official Certifier of Title Deeds (PPAT)	1.414

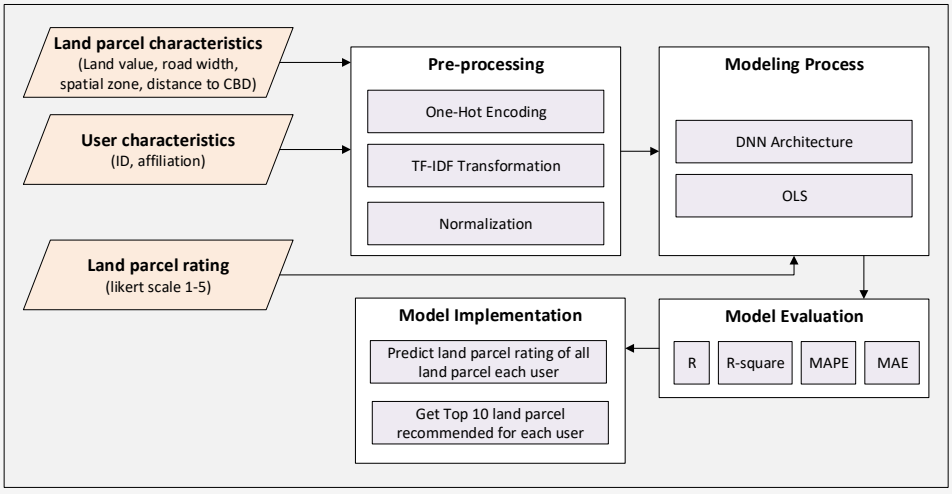


Figure 4: A recommendation system processing framework designed for a land parcel recommendation engine

For affiliation data, a Term Frequency-Inverse Document Frequency (TF-IDF) transformation process was carried out. In this study, TF-IDF was applied to the user occupation/affiliation field using scikit-learn's TfidfVectorizer. Each user affiliation was treated as a short document, while all affiliation records formed the document corpus. The vectorizer tokenized each affiliation string into unigram terms and computed TF-IDF weights across the corpus, producing a sparse user-by-term matrix. However, the full TF-IDF vector was not used as separate model inputs. Instead, the term-level TF-IDF weights for each user were summed row-wise to obtain a single scalar TF-IDF affiliation score. This scalar score was used as one numerical feature representing the user's professional affiliation in both the OLS and DNN models. TF-IDF is a statistical measure used to evaluate the relative importance of a term in a document with respect to a collection of documents. TF represents the frequency of a term within a document, while IDF represents the inverse frequency of the term across the document corpus, giving higher weights to terms that are more

distinctive. The TF-IDF calculation is shown in Equation 1 [24]:

$$TF - IDF = C_i \log\left(\frac{T}{t_i} + \gamma\right)$$

Equation 1

Where:

C_i is the number of occurrences of the feature word in the document
T is the total number of files
t_i is the document in which the feature word appears
γ is an empirical value that is usually given as 0.01

One hot encoding (OHE) was used to transform n-class categorical data into n columns filled with 1s and 0s. A value of 1 was assigned if the character appeared in a particular row, and 0 otherwise. OHE can be represented in the form of Equation 2 [25]:

$$OHE_j[k] = \begin{cases} 1, & if\ j = k \\ 0, & otherwise \end{cases}$$

Equation 2

Where $OHE_j[k]$ is the value of the jth OHE column of attribute k. OHE is used to transform ID data, resulting in n user columns

Data normalization was used to equalize the dimensions of numerical data. This was done to minimize prediction bias due to significant differences in data dimensions. Data normalization was performed using minmax scaling. This technique transforms all numerical data into a range of 0-1. This technique was applied after all data had been transformed into numerical data. The data normalizations equation can be seen in Equation 3 [26]:

$$X_{scaled} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Equation 3

Where:

X is the original value
X_{min} is the minimum value
X_{max} is the maximum value of a variable

The next phase is the land parcel rating prediction modelling phase. Two modelling approaches were employed, namely Ordinary Least Squares (OLS) regression and Deep Neural Networks (DNN). OLS regression was used as a baseline model to represent linear relationships between user preferences and land parcel attributes. The objective of OLS is to estimate regression coefficients that minimize the squared difference between observed and predicted user ratings. The mathematical formulation of the OLS estimator is presented in Equation 4:

$$\beta = \left[X^T X\right]^{-1} X^T Y$$

Equation 4

Where:

β is the vector of regression coefficients
X is the matrix of input features
Y is the vector of observed land value ratings
X^T is the transpose of the feature matrix.

In this study, the X and Y matrices are defined as shown in Equations 5 and 6, respectively.

$$X = \begin{bmatrix} 1 & ID_1 & W_1 & d_1 & Z_1 & O_1 & L_1 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ n & ID_n & W_n & d_n & Z_n & O_n & L_n \end{bmatrix}$$

Equation 5

$$Y = \begin{bmatrix} r_1 \\ \dots \\ r_n \end{bmatrix}$$

Equation 6

Where n is the total number of the parameters, ID is the user ID number, W is the width of the road, d is the distance to CDB, Z is the zoning score, O is the occupation, L is the land value, and r is the rating.

To model non-linear relationships, a Deep Neural Network (DNN) was developed as a single-output regression model for predicting continuous land parcel rating values. The DNN estimates the predicted rating $\hat{y}$ as a function of the input feature vector x, as expressed in Equation 7:

$$y = f_\theta(x)$$

Equation 7

Where:

$\hat{y}$ is the predicted land parcel rating
x is the input feature vector
θ is the trainable network parameters.

Deep neural networks (DNNs) transform input data through multiple hidden layers to learn hierarchical feature representations for prediction tasks. To accomplish this, neural networks rely on components known as activation functions [27]. These functions, including Sigmoid, Tanh, and ReLU, among others, form the core of neural network architectures.

The primary role of an activation function is to determine whether a neuron should be activated and to regulate the information passed through the network [28]. The proposed DNN follows a fully connected feedforward regression architecture comprising six hidden layers with a progressively narrowing structure: 256, 256, 128, 128, 64, and 64 neurons as pictured in Figure 5. The architecture of the DNN employed can be seen in Figure 4. Each hidden layer employs the Rectified Linear Unit (ReLU) activation function, defined in Equation 8:

$$f(x) = \max(x, 0)$$

Equation 8

ReLU was selected due to its computational efficiency and ability to mitigate vanishing gradient problems commonly associated with sigmoid and tanh functions [26][27] and [29]. Kernel weights were initialized using a normal distribution to ensure stable convergence during training. The output layer consists of a single neuron with ReLU activation, producing a continuous non-negative rating prediction. Therefore, the model estimates a continuous land parcel rating rather than a class probability distribution. The model was optimized using the Adam optimizer, which adaptively adjusts learning rates to accelerate convergence. Mean Absolute Error (MAE) was used as the loss function due to its robustness to outliers and interpretability. The model was trained using a batch size of 20 for 150 epochs, with performance evaluated on both training and testing datasets. To assess model performance, the dataset was divided into 80% training data and 20% testing data, a commonly adopted split that balances model generalization and evaluation reliability. The DNN was trained to predict continuous rating values based on the observed 1–5 Likert-scale ratings. In the reported evaluation, no additional clipping or rescaling was applied to force the predicted ratings into the 1–5 range. The predicted values were used directly for model evaluation and ranking. The ReLU activation function in the output layer imposed a lower bound of zero, preventing negative predictions, but it did not impose an upper bound of five. Therefore, although the predicted values generally fell within or near the observed rating range because the model was trained on 1–5 Likert-scale targets, this range was not formally guaranteed by the model architecture. For operational deployment, bounding or clipping predicted values to the valid rating interval [1] and [5] may be considered to improve interpretability and consistency with the original rating scale.

Model performance was evaluated using four metrics: correlation coefficient, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2) [30] and [31]. These metrics provide complementary insights into prediction accuracy, error magnitude, and explanatory power. The final data processing stage in this study was model implementation. There were two main processes in the model implementation stage, namely predicting ratings for all land parcels for each user and providing the top 10 land parcel recommendations for user-i. Model prediction implementation was carried out on the entire data set by combining all user data and land parcel data. The scheme for combining the two data sets can be seen in Figure 6. The land parcel data dimension is $n \times 5$ then concatenated with the user feature $m \times 2$ dimension, resulting in parameter data with $(m * n) \times 7$ dimension. The model is implemented to predict land parcel ratings on $(m * n) \times 7$ dimensional data. The output at this stage is a map of predicted land parcel ratings for each user. The second step in the implementation process of the model was to obtain the top 10 land parcel recommendations. The techniques used in this stage were sorting and filtering. The sorting and filtering techniques used can be written in pseudocode in algorithm shown in Table 2. The input for this algorithm was the desired user ID and the land parcel rating prediction dataset. The output of this algorithm was the top 10 land parcel recommendations for a specific user ID.

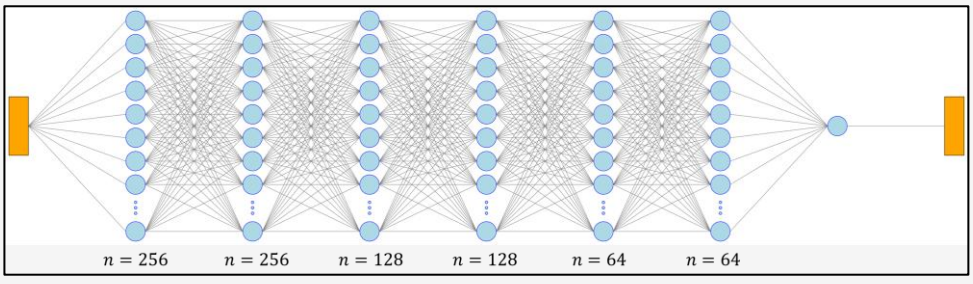


Figure 5: DNN architecture employed consists of six hidden layers

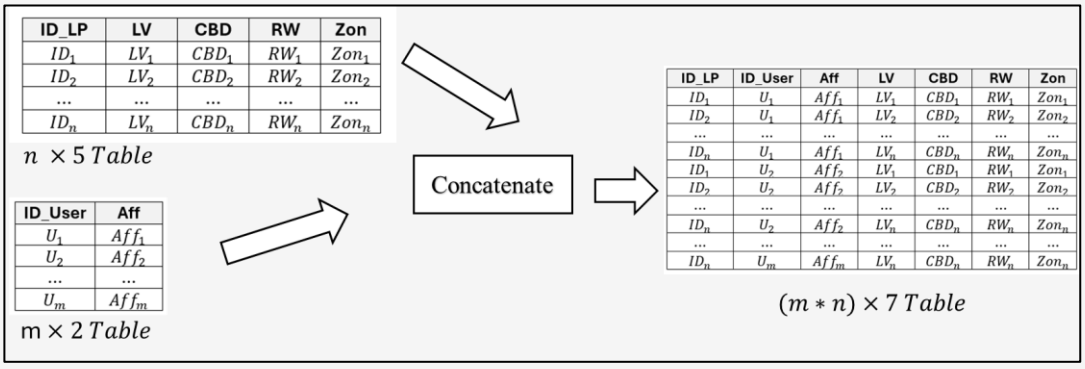


Figure 6: Scheme for merging user data and land parcel items

Table 2: Algorithm used to sort and filter user ID and land parcel rating prediction

Algorithm 1: Get top 10 recommendation

Input :

ID : User identifier

P : Dataset of land parcel rating prediction

$P = \{ Id_{user}, Rating_{prediction}, ID_{landparcel}, Landvalue, Location\}$

Output :

TOP_{10} : Top 10 land parcel recommendation

begin

// User-based filtering

$D \leftarrow \{p \in P \mid p \cdot ID_{user} = ID\}$

// Sort by rating prediction

$D \leftarrow sort\{D, key = Rating_{prediction}, order = decending\}$

// Top 10 selection

$T_{10} \leftarrow D[1:10]$

//Feature extraction

$F \leftarrow \{ID_{landparcel}, Landvalue, Location\}$

return $T_{10}F$

end

3. Results and Discussions

3.1 Model Performance

The performance of the OLS and DNN models was evaluated using four metrics: correlation coefficient, coefficient of determination (R^2), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The comparison of evaluation results for both training and testing datasets is presented in Table 3. Overall, the DNN model showed better predictive performance than OLS in the current train-test split experiment. For the training dataset, the DNN achieves a correlation coefficient of 0.96 and an R^2 value of 0.92, higher than those obtained by OLS (0.82 and 0.67, respectively). This indicates that the DNN is more effective in capturing the underlying relationships between user preferences and land parcel attributes. In terms of error metrics, the DNN also yields lower MAE (0.18) and MAPE (0.04) values than OLS, confirming its higher accuracy during training. For the testing dataset, both models exhibit a decrease in performance, which is expected when applied to unseen data. The DNN maintains a higher correlation coefficient (0.76) and R^2 value (0.57) compared to OLS (0.72 and 0.51, respectively), while also achieving lower MAE and MAPE values. These results suggest that although the DNN model experiences a more pronounced performance drop between training and testing, it still showed better predictive accuracy than OLS in this experimental setting. Conversely, OLS exhibits smaller variations between training and testing results, indicating greater stability but lower explanatory power

Table 3: Comparison of evaluation metrics value

Evaluation Metrics	OLS		DNN	
	Train Data	Test Data	Train Data	Test Data
Coefficient Correlation	0.82	0.72	0.96	0.76
R-Squared	0.67	0.51	0.92	0.57
Mean Absolute Error	0.32	0.35	0.18	0.28
MAPE	0.09	0.08	0.04	0.07

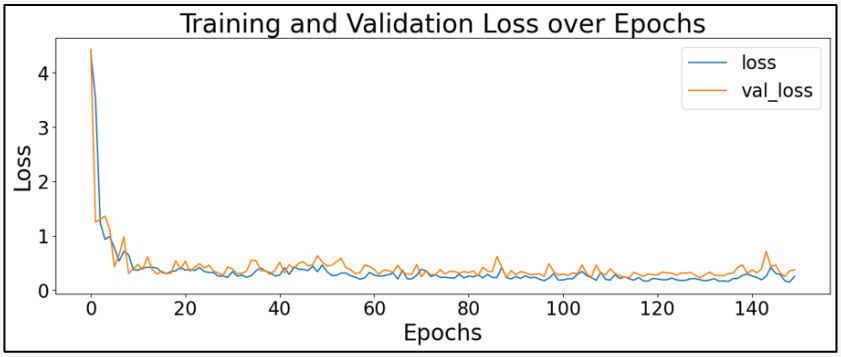


Figure 7: Training and validation loss of DNN Model

3.2 Loss Curve Analysis

The training dynamics of the DNN model are illustrated by the loss curves shown in Figure 7. Both training and validation loss decrease rapidly during the initial epochs, indicating effective learning of data patterns. As training progresses, the loss curves gradually converge and remain closely aligned, suggesting that the model generalizes reasonably well to unseen data. The absence of a substantial divergence between training and validation loss indicates that severe overfitting does not occur, although some performance degradation is observed in the testing phase. This behaviour is consistent with deep learning models trained on relatively limited datasets, where strong fitting to training data may reduce generalization performance [28] and [34]. Nevertheless, the convergence behaviour confirms that the selected architecture and optimization strategy are appropriate for the problem domain.

3.3 Feature Importance

Feature importance analysis was conducted using a unified permutation importance approach for both the OLS and DNN models to ensure comparability across the two modelling approaches. Each input feature was randomly permuted while the remaining features were kept unchanged, and the resulting decrease in predictive performance was measured using a mean-squared-error-based scoring function. The permutation procedure was repeated 10 times, and the average decrease in performance was used as the raw importance score. For both OLS and DNN, the reported values therefore represent normalized performance decreases caused by feature permutation, rather than raw regression coefficients, standardized coefficients, R^2 contributions, SHAP values, or Integrated Gradients. After computing the raw permutation scores, the one-hot encoded User ID variables were aggregated into a single User ID importance value, and all final importance values were normalized to sum to one. The importance values derived from both models are summarized in Table 4.

In the OLS model, User ID overwhelmingly dominates the prediction process, accounting for 95.4% of the total feature importance. Spatial attributes such as road width, zoning score, and distance to the CBD contribute negligibly. This indicates that the OLS model primarily relies on user-specific preference patterns and assigns minimal weight to spatial and economic characteristics of land parcels. In contrast, the DNN model distributes importance more evenly across features. UserID emerges as the most influential variable, followed by distance to CBD and zoning score, road width and TF-IDF affiliation still contribute significantly but less influential relatively compare with other variables. This distribution demonstrates the DNN's ability to integrate user preferences with spatial and contextual attributes, enabling more comprehensive modelling of land value perceptions. The results suggest that DNN captures complex interactions between user characteristics and land parcel features that linear models such as OLS are unable to represent effectively.

Table 4: Feature importance of OLS and DNN model

Variables	Feature Importance	
	OLS	DNN
UserID (*ID*)	0.954	0.215
TF_IDF Affiliation	0.046	0.113
Road Width (*W*)	5.31×10^{-29}	0.133
Zoning Score (*Z*)	2.88×10^{-29}	0.174
Distance to CBD (*d*)	2.10×10^{-29}	0.211
Land value prediction (*L*)	1.712×10^{-29}	0.154

3.4 Spatial Visualization of Results

To further examine model behaviour, predicted land value ratings were visualized spatially in the form of Rating Prediction Maps and Top 10 Recommendation Maps. Both OLS and DNN models were applied to predict ratings for all land parcels in the study area. The top 10 land parcel recommendations were presented to balance recommendation relevance and practical usability. This number is sufficient to provide users with multiple viable alternatives while avoiding information overload, thereby supporting effective decision-making in land parcel selection. We took 2 users as samples to visualize the overall result of each user, namely user 1 and user 17 within the study area. These users were chosen to illustrate contrasting recommendation patterns resulting from distinct user preference profiles, thereby enabling a clearer comparison of how each model responds to different user characteristics.

The prediction results considered user characteristics in terms of affiliation and land parcel characteristics in terms of physical properties and land value. The prediction map is presented as a visual aid that makes it easier for users to intuitively interpret the suitability level of each plot of land through spatial representation. Through this map, users can identify specific spatial distribution patterns or clusters within the map to see which areas are generally the best land parcel for users according to their respective preferences. To maintain positional accuracy, a local Coordinate Reference System (CRS) was used. The DGN95/ Indonesia TM-3 Zone 49.2 projection was used to visualize the results. The Rating Prediction Maps shown in Figure 8 reveal distinct spatial patterns between the two models. OLS predictions tend to exhibit relatively homogeneous spatial distributions, with limited variation across different areas. This reflects the model's reliance on global statistical relationships rather than localized spatial characteristics. In contrast, DNN predictions display greater spatial heterogeneity, capturing localized variations in land value assessments influenced by proximity to the CBD, road accessibility, and other spatial factors. The variations in colour-related patterns among users further highlight the DNN model's sensitivity to individual user preferences.

Figure 9 illustrates the comparison between land parcel recommendations generated by the OLS and DNN models for User 1. The OLS-based recommendations exhibit a strong tendency toward spatial clustering, with several recommended parcels located adjacent to one another, including Land Parcel IDs 84984–84985, 85172–85173, and 83868–83869. These parcels are concentrated within Gunung Anyar Tambak, Gunung Anyar Sub-district, and are characterized by similar estimated land values. This pattern indicates that the OLS model tends to generate recommendations with homogeneous spatial and valuation characteristics.

In contrast, the DNN-based recommendations for User 1 display substantially greater spatial diversity. The recommended parcels are distributed across multiple sub-districts, with top-ranked locations primarily found in Genteng, Simokerto, and Bubutan. Notably, Embong Kaliasin Village emerges as a prominent location for the highest-ranked parcel. Moreover, variations in parcel geometry and orientation suggest that the DNN model captures a broader range of spatial and geometric characteristics, enabling recommendations that reflect not only land value but also potential differences in land usability and accessibility. A similar trend is observed for User 17, as shown in Figure 10. The OLS model again produces relatively clustered recommendations, with parcels located in close proximity and exhibiting similar spatial characteristics. Conversely, the DNN model generates more heterogeneous recommendation patterns, with parcels that are more dispersed and varied in terms of spatial distribution and parcel identity. This consistency across User 1 and User 17 reinforces the finding that OLS tends to produce more uniform and spatially concentrated recommendations, whereas DNN provides more diverse, flexible, and personalized recommendation outcomes.

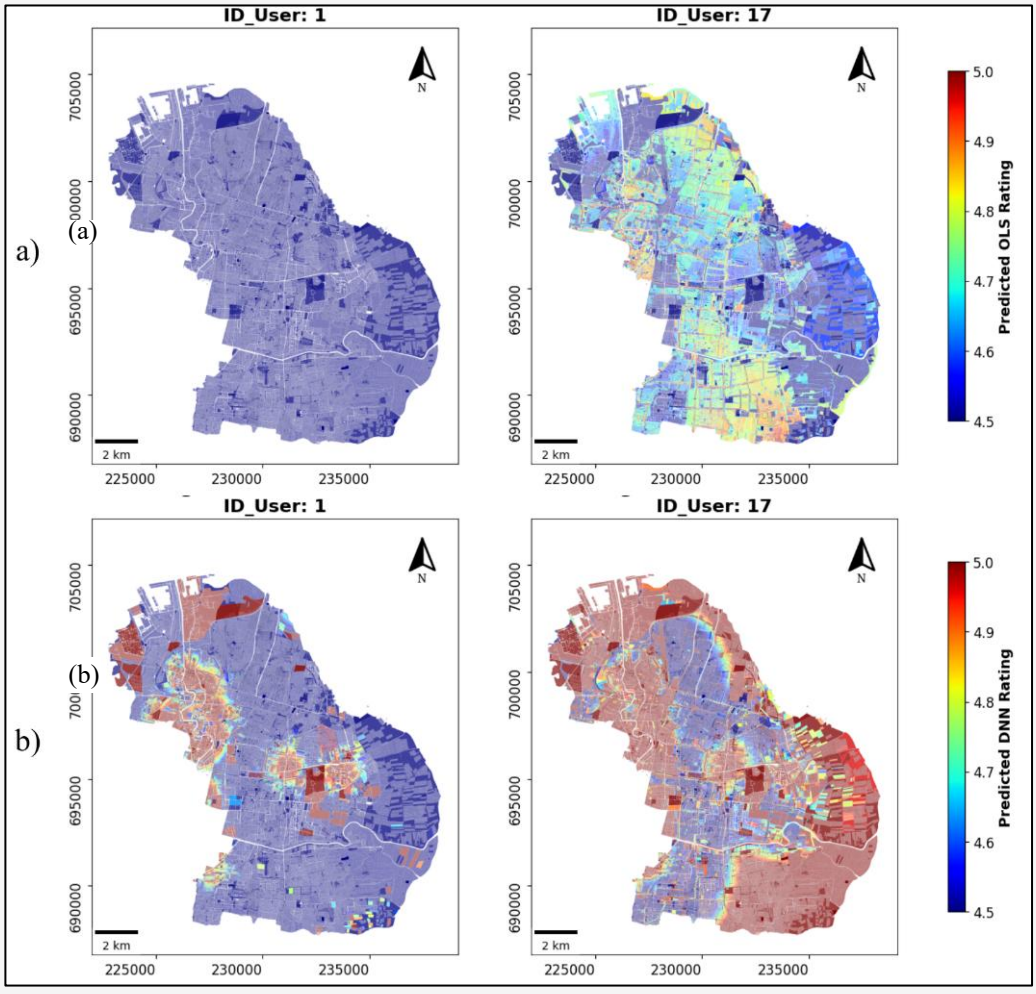


Figure 2: Users' rating prediction map using: (a) OLS model and (b) DNN model

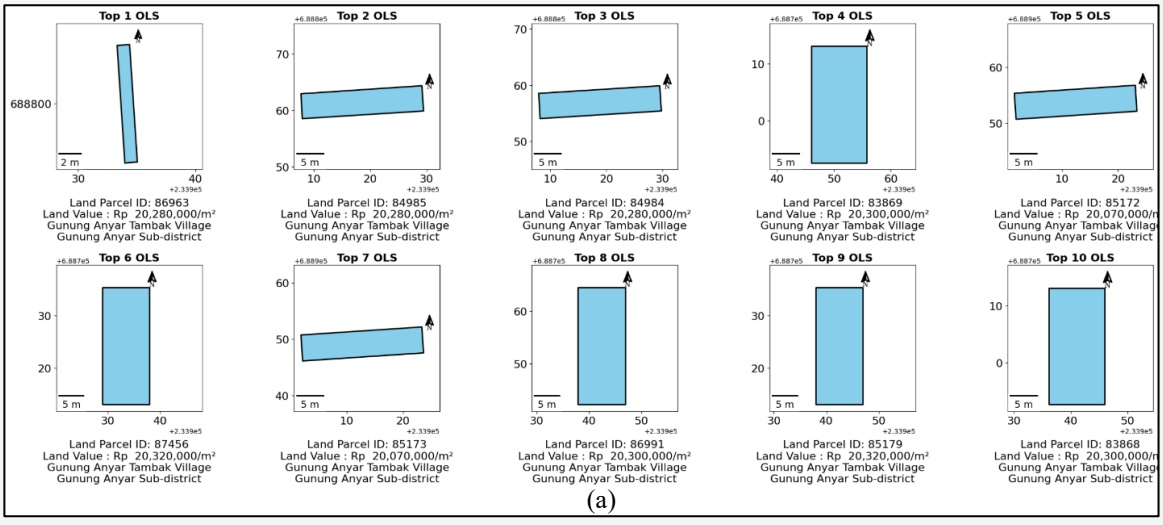
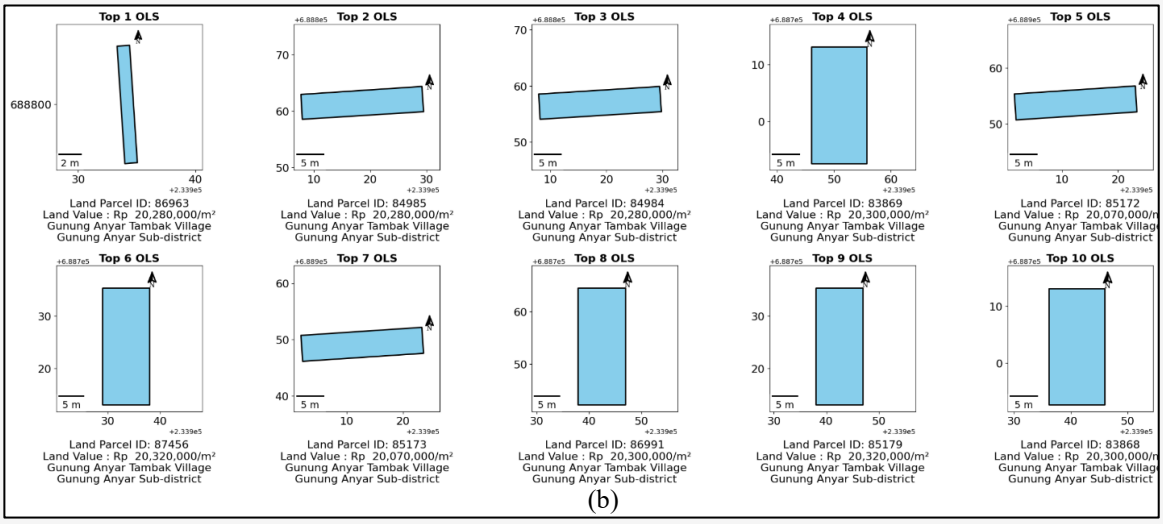
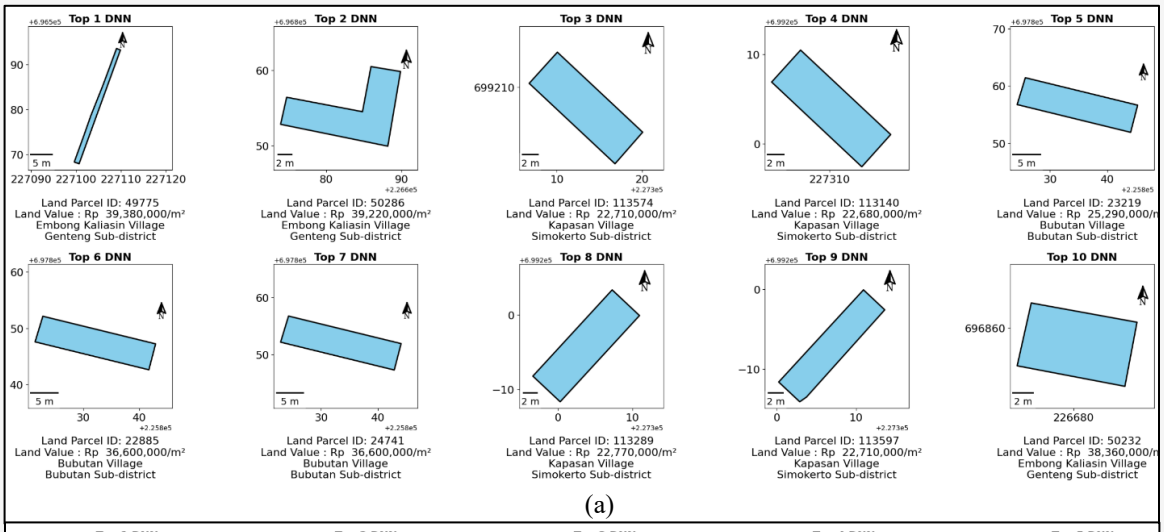


Figure 3 : Top 10 user's land parcel recommendation for: (a) user 1
(continue next page)

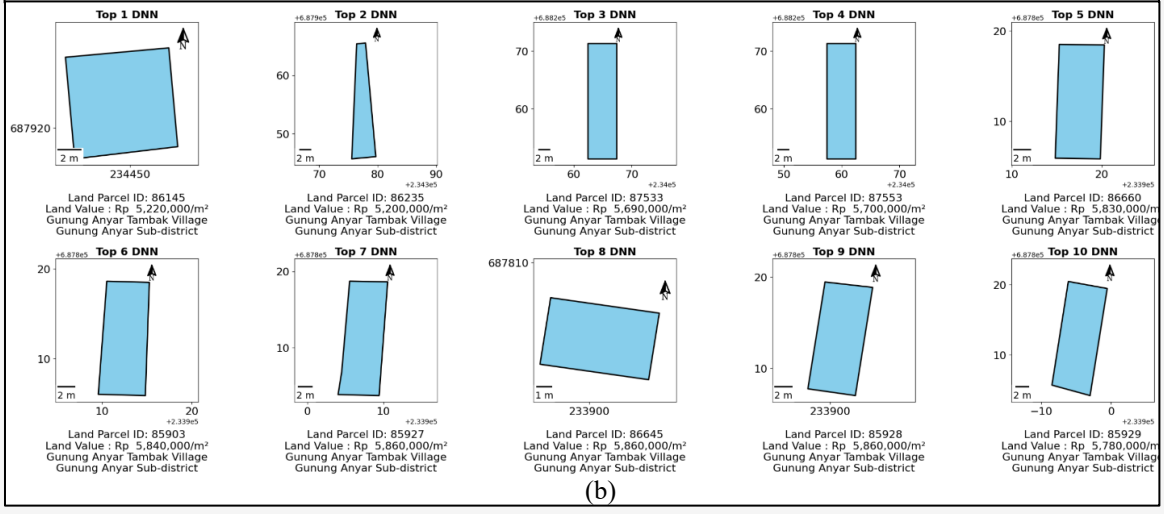


(b)

Figure 4 : Top 10 user's land parcel recommendation for: (b) user 17
(continue from previous page)



(a)



(b)

Figure 5: Top 10 user's land parcel recommendation for: (a) user 1, and (b) user 17

3.5 Discussions

The comparative analysis between Ordinary Least Squares (OLS) and Deep Neural Network (DNN) models reveals distinct mechanisms by which user preferences and spatial characteristics are translated into land parcel recommendations. Although both models utilize identical input features, their resulting recommendation patterns diverge substantially regarding spatial concentration, diversity, and interpretability. OLS-based recommendations exhibit a pronounced tendency toward spatial clustering, with suggested parcels frequently located in close geographic proximity and sharing similar value characteristics. This behaviour is attributable to the linear structure of the OLS model, which emphasizes proportional relationships between input variables and predicted ratings. Consequently, parcels with comparable spatial attributes are consistently ranked highly. While such clustering may benefit applications requiring neighbourhood consistency, it inherently restricts the exploration of alternative parcels that differ in spatial configuration yet remain aligned with user preferences.

In contrast, DNN-based recommendations demonstrate greater spatial dispersion and heterogeneity. Recommended parcels are distributed across multiple sub-districts, exhibiting significant variation in geometry, orientation, and spatial context. This indicates that the DNN model more effectively captures complex, non-linear interactions among spatial attributes, land value indicators, and user preferences. Rather than relying primarily on spatial proximity, the DNN model balances multiple factors simultaneously, allowing parcels with distinct spatial characteristics to emerge as competitive recommendations.

These findings remain consistent across multiple users, suggesting that the observed differences are inherent to the modelling architectures rather than individual rating behaviours. The recurrence of clustered recommendations in OLS and diverse recommendations in DNN implies that linear models may be insufficiently robust to represent the complexity of land-related decision-making. Land parcel selection involves intricate trade-offs between accessibility, zoning constraints, geometry, and economic factors nuances that linear relationships often fail to capture adequately.

Methodologically, these results align with prior studies highlighting the efficacy of deep learning in spatial prediction tasks [35] [36] and [37]. Deep neural networks have frequently outperformed traditional regression-based approaches in contexts characterized by high-dimensional data and non-linear dependencies. In this study, the high capacity of the DNN model enables a more effective integration of spatial and user-related information, resulting in recommendations that better reflect the multidimensional nature of land suitability. Beyond methodological performance, these findings hold practical implications for land valuation and decision-support systems. In domains such as property investment and urban planning, stakeholders often require a spectrum of viable alternatives rather than a narrow set of spatially homogenous options. The diversity observed in DNN-based recommendations suggests that AI-driven models can facilitate exploratory decision-making by presenting a broader set of feasible parcels. Conversely, the spatial clustering produced by OLS remains valuable in scenarios prioritizing neighbourhood consistency or localized development strategies.

Despite these contributions, several limitations must be acknowledged. First, recommendation quality is contingent upon the availability and reliability of user rating data, which may be influenced by subjective judgment and sample size limitations. This study did not perform retraining-based ablation experiments by excluding User ID, using only affiliation features, or removing predicted land value from the feature set. Therefore, future studies should conduct feature-exclusion experiments to more explicitly assess the model's reliance on user-specific and land-value-related variables. This study was also limited to an initial comparison between OLS and DNN and did not evaluate smaller-capacity tabular models such as Random Forest, Gradient Boosting, XGBoost, LightGBM, or CatBoost. Future studies should compare these models to assess whether similar or better predictive performance can be achieved with lower model complexity and improved interpretability.

The current prototype is limited to users and affiliation terms represented in the training data, since User ID was encoded using one-hot encoding and TF-IDF was fitted on the available affiliation corpus. Future deployment should include cold-start strategies for new users and unseen affiliations, such as generalized professional categories or initial preference elicitation. Second, as this study focuses on a single urban area, the generalizability of findings to cities with differing spatial structures and market dynamics requires further validation. Finally, while the DNN model produces more diverse recommendation patterns, its reduced interpretability compared to OLS "black box" nature may pose adoption challenges in operational settings where transparency is paramount.

Overall, this discussion underscores the importance of selecting recommendation models that

align with both data characteristics and decision-making objectives. The results indicate that deep learning–based approaches offer substantial advantages for personalized land parcel recommendation in complex urban environments, while simpler linear models retain a complementary role depending on specific application requirements.

4. Conclusions

This study proposes and evaluates an AI-based land parcel recommendation framework utilizing a Feature-based Multi-Criteria Recommendation System (FMCRS) approach, integrated with spatial and economic attributes. The framework was validated through a case study in Surabaya City, which compared the performance of Ordinary Least Squares (OLS) regression and a Deep Neural Network (DNN) model in predicting user ratings and generating personalized land parcel recommendations. Empirical results indicate that while both models generate viable recommendations, they exhibit distinct behavioural characteristics. The OLS model tends to produce spatially clustered recommendations with relatively homogeneous land parcel attributes, reflecting its reliance on linear relationships. In contrast, the DNN model yields spatially diverse and flexible recommendations, demonstrating a capability to capture non-linear interactions between user preferences and land parcel characteristics. These findings suggest that deep learning–based approaches are effective for personalized land parcel recommendation tasks, particularly in complex urban environments where decision-making involves multiple interrelated spatial factors. The proposed framework highlights the potential of synthesizing AI-driven recommendation techniques with geospatial data to enhance land valuation and parcel selection processes. Future research should extend this work by incorporating additional user preference variables, exploring alternative deep learning architectures, and evaluating the system across diverse urban contexts. Furthermore, enhancing model interpretability and integrating interactive user feedback mechanisms represent promising directions for continued development.

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