Artificial Neural Network Approach for Predicting the Land Values for Blocking-Out Diagrams.

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Abstract: *Land valuation is a complex and subjective process influenced by various global and local economic conditions, such as income levels, population trends, unemployment rates, interest rate movements, transportation infrastructure, and urban planning policies. Physical attributes like size, shape, road frontage, and number of corners also contribute to the uniqueness of each parcel, directly affecting land demand. This study examines advanced valuation approaches using Artificial Neural Networks (ANN) as a decision support tool to estimate accurate and reliable land values. The ANN techniques were applied to two datasets from the Colombo area in Sri Lanka, comprising 24 lots from Kidelpitiya and 143 lots from Meepe. The model considered factors such as extent, accessibility, class, and distance from entrance, number of access sides, road frontage, nature, price of bare land, and price of developed land. The ANN model showed improved prediction accuracy with statistical metrics of RMSE = 0.24505, MAE = 0.17541, and MSE = 0.06005. The model achieved a 96% accuracy level according to the RICS property regulation tolerance value (15%), making it suitable for residential land valuation in real estate appraisal.*

Keywords: *ANN, Land subdivision, Land valuation, Real estate, Price prediction.*

Introduction

The process of property valuation is a complex one, involving the assessment of various economic conditions at global, national, regional, and local levels. Factors such as income level, population trends, unemployment rates, and interest rate movements are inspected as they directly influence the demand of the property market under consideration (Eke & Ashamu, 2009). The land valuation criteria can be divided into four groups: physical attributes, legal factors, locational characteristics, and economic conditions (Branković et al., 2015).

Traditionally, property valuers have relied on manual assessment methods. These include the comparative method, investment method, profits method, residual method, and contractor's method (Pagourtzi et al., 2003). However, these traditional approaches are prone to relatively high levels of inaccuracy (Zurada et al., 2006; Aluko, 2007; Paris, 2008).

In response to the limitations of traditional methods, the valuation industry has seen a surge in data availability and the growth of information technology, facilitating the development of advanced valuation methods (Wilkinson et al., 2018). These include leveraging artificial intelligence (AI) such as artificial neural networks (ANN), expert systems (ES), and fuzzy logic systems (FLS) (Pagourtzi et al., 2003). Researchers have demonstrated that these technology-based approaches, especially AI methods, offer improved accuracy and efficiency (Taffese, 2006; Chaphalkar & Sandbhor, 2013; Morano et al., 2015; Abidoye & Chan, 2017a).

Given these challenges, there is a growing consensus that the purpose of property valuation estimates required by valuation clients should shift to advanced property valuation processes (Gilbertson and Preston, 2005). This study aims to examine the advanced valuation approaches with a focus on the artificial neural network (ANN) technique, which could serve as a decision support tool to estimate accurate and reliable property valuation figures.

Artificial Neural Networks (ANN) are a multivariate analytical tool that promises to become the next major tool used for computerized mass appraisal (Tay, 1992). An artificial neural network is a system of artificial intelligence model that replicates the working process of the human brain. The ultimate goal of the model is to predict the accurate answer as the output, rather than the specific relationship between the input and the output response (Worzala, Lenk and Silva, 1995d).

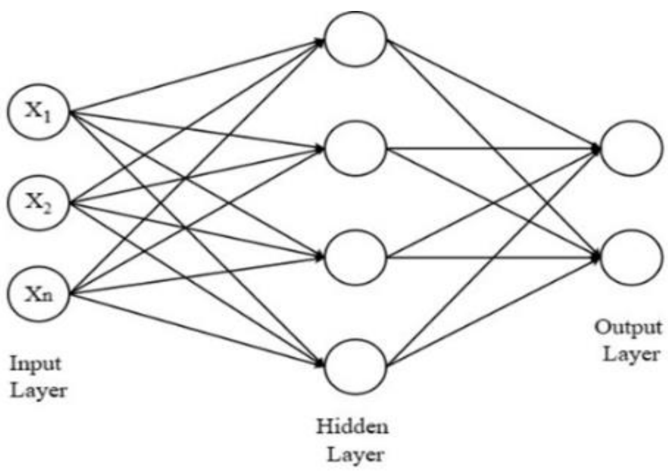

Figure 1: Structure of the ANN model

An artificial neural network consists of three types of layer structures of nodes: the input layer or layers, the hidden layer or layers, and the output layer. The input layer is filled with data derived from independent variables and the output layer symbolizes the dependent. The ultimate aim of the artificial neural network model is to ensure that the influence of these weights produces a response that mirrors the actual relationship between the input independent variables and the output dependent variables. In most research, the initial neural network model is created utilizing a training set of input and output data variables (Worzala, Lenk and Silva, 1995d).

Literature Review

Traditional methods of property valuation primarily rely on direct comparisons, where the valuer draws conclusions about the value of the subject property (Yacim and Boshoff, 2014). However, scholars have criticized these traditional methods, arguing that they often fail to produce accurate and reliable valuation estimates (Ratcliff, 1972; Zurada et al., 2006). This criticism stems from the subjective nature of these approaches, as their outputs heavily depend on the skills and experience of the valuer (Paris, 2008).

Despite the advancements in property valuation methods, traditional property valuation still faces challenges. Studies have shown inaccuracies in different property markets around the world at different levels (Mallinson and French, 2000). The process is also time-consuming and costly due to its reliance on manual methods and physical site inspections. For instance, in Cyprus, determining market value involves a hands-on approach where every parcel undergoes visual inspection, forming a sort of mass land appraisal. However, this method suffers from various drawbacks, including issues with time consumption, excessive costs, lack of transparency, accuracy concerns, reliability issues, inconsistency, and fairness (Demetriou, 2016).

In the real estate sector, land subdivision layout is a crucial aspect that can benefit from development techniques. As the demand for land continues to increase rapidly, there's a growing necessity to evaluate the efficiency of land subdivision layouts. Effective land subdivision involves transforming traditional parcel arrangements into more practical and comfortable living areas (Adams et al., 2013). Subdivision layouts can be generated either to achieve the maximum number of lots or an optimal balance between number of lots and new streets. Hence, parcel subdivision can impact neighboring parcels due to shared streets (Brobst and Gates, 1978).

In all artificial neural network (ANN) models, the slopes of the best fits closely approximate 1 when tested with the training data itself. The coefficient of determination (R2), which indicates the proportion of the variance in the dependent variable that is predictable from the independent variable(s), was also utilized as a measure of model performance. The RMSE value represents the predicting error such that the model with less RMSE value is more successful in prediction than the model with higher RMSE. (Yalpır, 2016b). The models' performance was evaluated by calculating the mean absolute error between the predicted values and the actual sales prices for each model (Rossini, 1997).

For modeling purposes, data from 98 parcels were utilized, which were subsequently divided into two subsets: 76 for training and 22 for testing. Both training and testing datasets were organized to ensure a homogeneous distribution of parcels across the region. Input variable properties were obtained from map information, while unit market value data was sourced from land agencies (Yalpır, 2016c). During the model training phase, the dataset was randomly divided into three parts. Training set was contained 60% of the sample while 20% was designated for the 'validation set'. The remaining 20% was reserved for the 'test set' (Mimis, Rovolis and Stamou, 2013c).

The input data is normalized before feeding it into the network. This normalization helps in handling data between -1 and 1, which is the range that backpropagation algorithm can handle. Data preprocessing encompasses the preparation of data for model training through cleaning, transforming, and organizing it. In the context of land valuation, the initial step involved normalizing the data to a range of using a specific equation Yalpır (2016). The initial database used in the study was pre-processed by data cleaning, which involved detecting and removing inaccurate or incomplete records. Empty cells and errors in addresses were the most common problems (Mimis, Rovolis and Stamou, 2013b).

Processed signals exit the network through the output layer. Neural networks are categorized by architecture (feedforward, feedback, or competitive) and learning process (supervised or unsupervised). Training involves providing the network with input-output pairs and adjusting synaptic weights to match predicted outputs (Mimis, Rovolis and Stamou, 2013b).

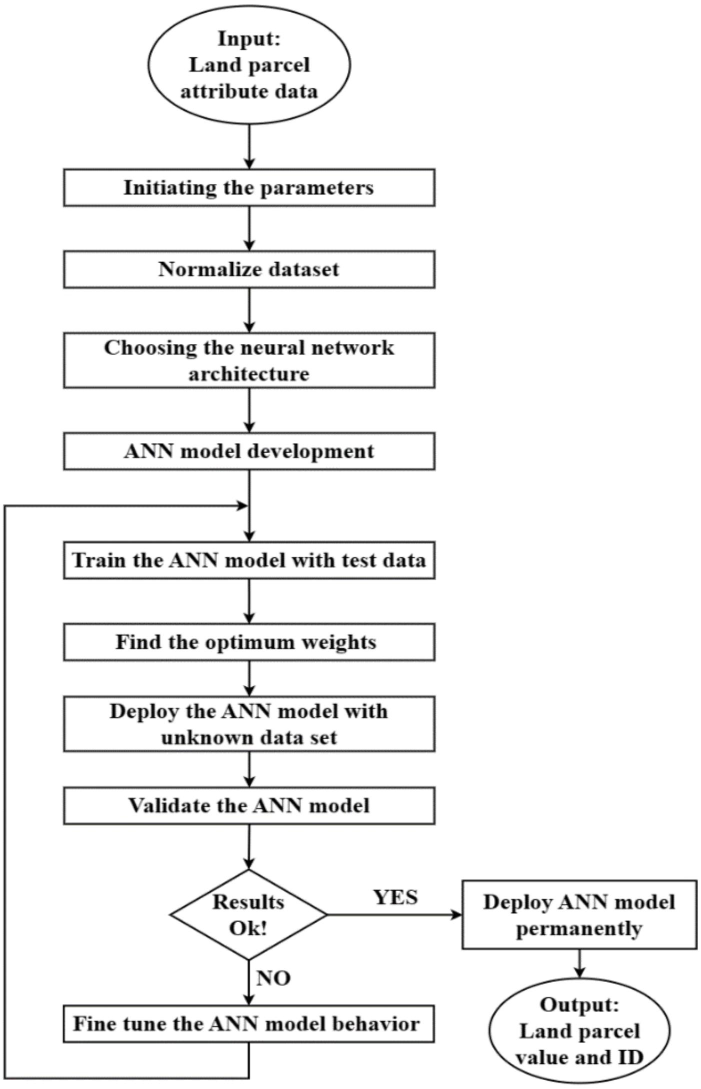

Figure 2: Methodology diagram

Following resources were used to create the database that supports the Artificial Neural Network (ANN) model:

1. **CAD Drawings of Blocking-Out Diagrams**:
   This was a crucial requirement for the research as it facilitated the identification of various land properties that affect land value. Parameters such as the extent (area),

distance from the entrance, road frontage, width, and length were measured using these drawings.

2. **Layout of Blocking-Out Diagrams**:
   Hard copies of the blocking-out diagrams were utilized to determine other critical parameters, including shape, accessibility class, number of access sides, and the nature of the land.

3. **Price List of Individual Land Parcels**:
   These values were essential for training and validating the ANN model, serving as output data.

4. **General Land Value**:
   This value was determined based on market surveys.

The parameters were selected using two methods to capture the physical characteristics of the land:

1. **Expert Opinions**: Input was gathered from professionals in the real estate sector, licensed surveyors, and academics specializing in surveying and land management at the Faculty of Geomatics, Sabaragamuwa University of Sri Lanka (SUSL).

2. **Literature Review**: Relevant literature was reviewed, particularly studies related to parcel-based land valuation, such as those examining the impact of subdivision layouts on market values.

Based on these criteria, the following parameters were selected:

1. **Extent**: Measured as the total area of the land parcel.

2. **Shape**: Categorical classification of the land's form.

3. **Accessibility Class**: The ease of access to the land parcel.

4. **Nature**: Represents specific features, such as whether a paddy field is near the boundary of the land, represented in binary form (e.g., 1 for presence, 0 for absence).

5. **Distance from Entrance**: The distance from the main entrance to the land parcel.
6. **Number of Access Sides**: Indicates the availability of roads near the boundary, described by the number of access points.
7. **Road Frontage**: The length of the side of the land parcel that fronts a road, measured as a fraction of the perimeter.
8. **Price of Bare Land**: The value per unit of undeveloped land.
9. **Price of Developed Land**: The value per unit of developed land.

Each parameter plays a significant role in determining the land's value. For example, the extent measures the total area, while the shape is categorized based on the land's configuration. The "nature" parameter identifies unique features like proximity to a paddy field, and "distance from the entrance" measures accessibility from the main entrance. The "number of access sides" reflects the availability of surrounding roads, and "road frontage" quantifies the road-facing length, which is crucial for evaluating the land's exposure and value. The prices of bare and developed land provide an economic valuation benchmark, which is essential before applying the blocking-out process.

Data normalization

Normalization is a crucial data preparation technique frequently used in machine learning to standardize the scale of input data. In this study, the Min-Max scaling method was applied to normalize the dataset. This method involves transforming each value in a column to a common scale, ranging from 0 to 1.

To perform Min-Max normalization, the difference between the maximum and minimum values in each column is calculated. Each value in the column is then adjusted by subtracting the minimum value and dividing by the range (the difference between the maximum and minimum values). This process ensures that all data values are scaled proportionately, facilitating effective model training.

The formula for Min-Max normalization is:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

Modeling

The valuation system is based on a Feedforward Neural Network (FNN) architecture, where information flows in a single direction: from the input nodes, through the hidden nodes, and finally to the output nodes. In this architecture, each layer of nodes is fully connected to the next, allowing the model to learn complex patterns in the data.

The neural network in this study is structured with one input layer containing 8 nodes, which represent the input features (parameters). These input nodes feed into a series of hidden layers that further process the information. The network comprises seven hidden layers, each designed to capture different levels of abstraction from the input data. Finally, there is a single output layer with one node, which produces the predicted value for the relevant land parcel.

The output neuron represents the model's prediction for the land value, taking into account all the input parameters and the learned relationships between them. The feedforward design ensures that the data moves in one direction—from inputs to outputs—enabling the network to predict land values effectively based on the provided features.

Study area

Two land sites in Colombo district that compromising 24 and 143 land parcels.

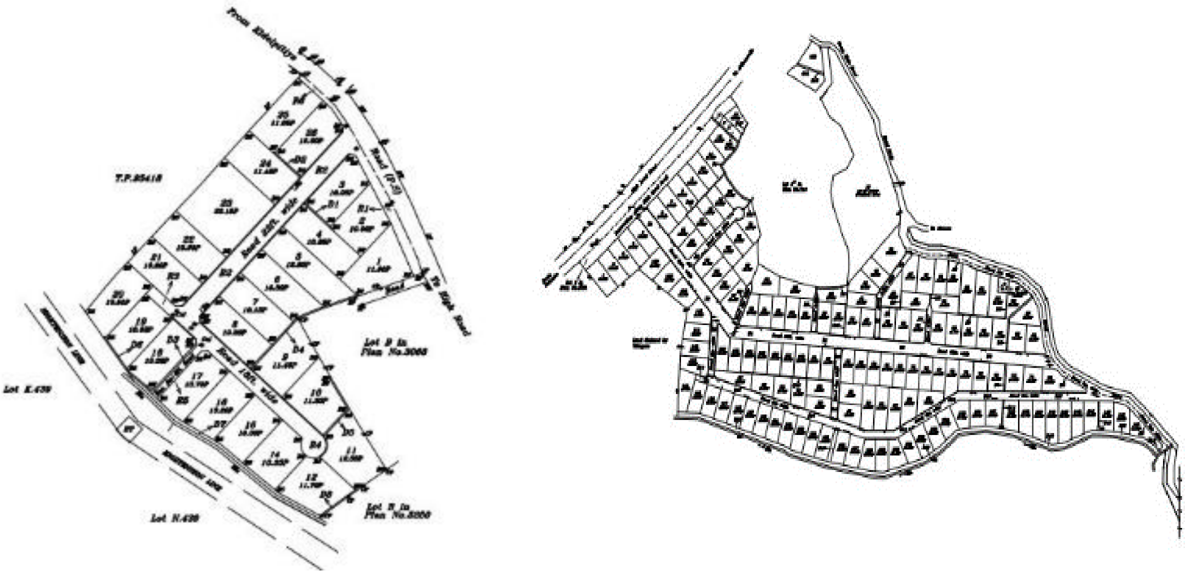

Figure 3: Blocking-Out Diagram

Training Process

The model was initially trained using independent datasets. The Artificial Neural Network (ANN) was trained using the backpropagation algorithm, which adjusts the model's weights to minimize the error between predicted and actual values. The weights were initialized using the Xavier initialization method to ensure that the initial weights were set appropriately, preventing issues related to vanishing or exploding gradients during training.

The dataset was split into training and testing subsets, with 80% of the data used for training and the remaining 20% reserved for testing. The model was trained for 100 epochs, with a batch size of 32. The number of epochs and the batch size were determined by experimenting with different values to optimize model performance, guided by analyzing the training loss and validation loss curves.

The Adam optimizer was selected for this task due to its adaptive learning rate capabilities and its efficiency in handling complex optimization problems. Throughout the training process, the model parameters were fine-tuned with each epoch, gradually converging towards optimal solutions to improve prediction accuracy.

Data validation

During the training phase, a portion of the data, specifically 20% of the training dataset, was set aside for validation purposes. This validation data is used to optimize the model's parameters and to prevent overfitting, ensuring that the model generalizes well to unseen data.

Throughout the validation process, key performance metrics such as accuracy, loss, and validation error were continuously monitored to assess the model's performance and make necessary adjustments. By evaluating these metrics, the model's ability to make accurate predictions on new data was carefully assessed and fine-tuned.

Finally, the predicted values were inverse-scaled to return them to their original scale, allowing for a direct comparison with the actual values and a clearer assessment of the model's predictive accuracy.

Statistical analyze of model performance

To evaluate the performance of the model, two key statistical metrics were used: Mean Absolute Error (MAE) and Mean Squared Error (MSE).

Mean absolute error (MSE): MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average absolute difference between the predicted values $(\hat{Y}_i)$ and the actual values (Y_i). (n) is number of observations. A lower MAE value indicates better accuracy of the prediction method.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right| \qquad (2)$$

Mean squared error (MSE): MSE measures the average of the squared differences between predicted values $(\hat{Y}_i)$ and actual values (Y_i). (n) is number of observations. It gives a higher weight to larger errors due to the squaring of the differences, making it particularly sensitive to outliers. A lower MSE indicates that the model's predictions are closer to the actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \qquad (3)$$

Root Mean Square Error (RMSE): RMSE represents the square root of the average of squared differences between the predicted values $(\hat{Y}_i)$ and the actual values (Y_i). (n) is number of observations. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2} \qquad (4)$$

Results and Discussion

Dataset comparison

The model was trained separately on two datasets, as described in the methodology. The performance of the model was evaluated using several criteria, including statistical metrics and weight comparisons.

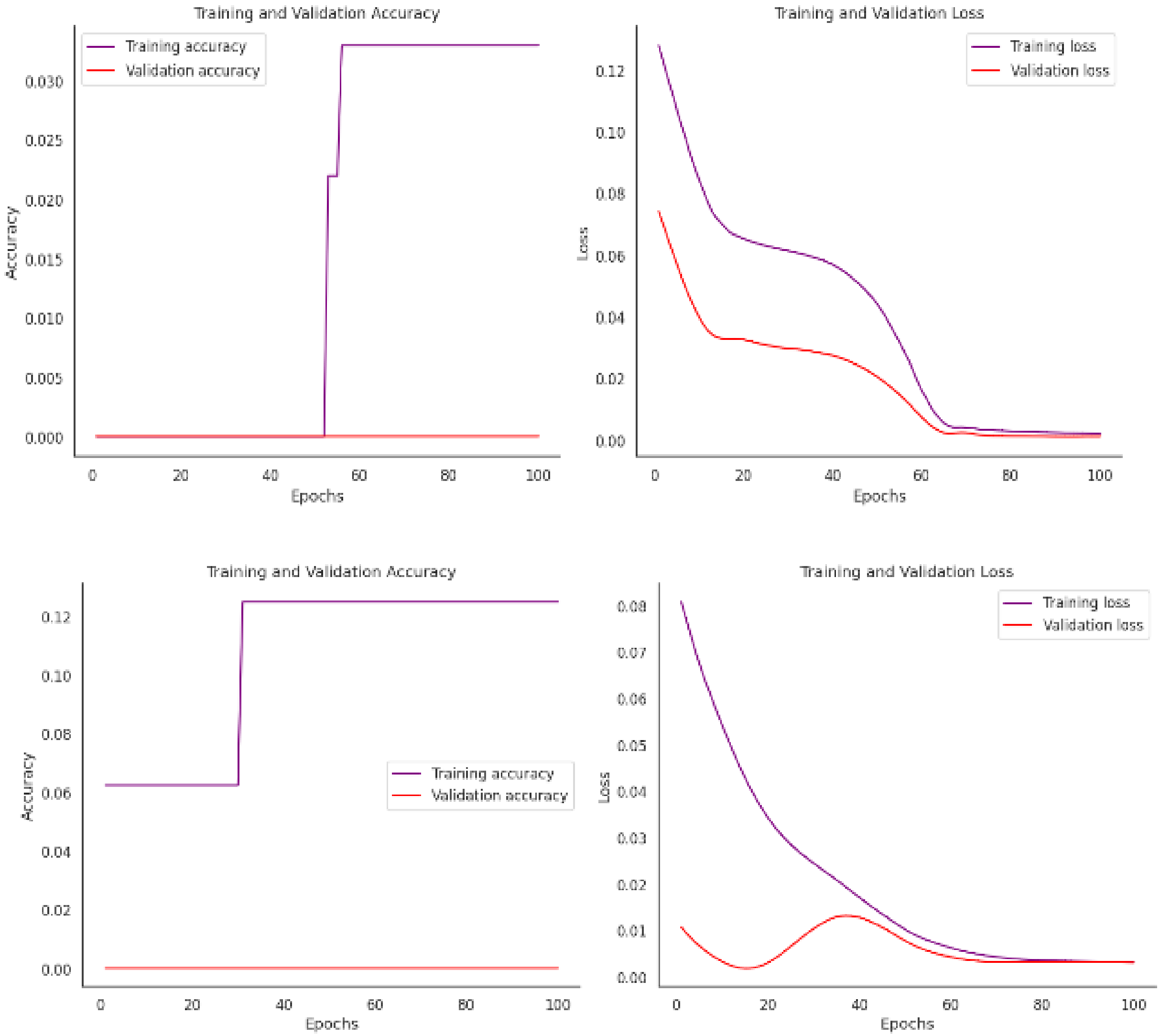

Figure 4: Training curve and validation curve of Meepe(left) and Kidelpitiya(right)

During this phase, the predicted values were compared with the actual values. A lower Mean Absolute Error (MAE) indicates smaller deviations between the predicted and actual values.

Table 1: Evaluation matrix of individual dataset

	Kidelpitiya	Meepe
MAE	0.18819	0.03758
MSE	0.05760	0.00229
RMSE	0.24000	0.04788

Prediction evaluation

The maximum and minimum differences between predicted and actual values for Kidelpitiya land were Rs 804,250 and Rs 103,000, respectively. For Meepe land, these differences were Rs 1,257,000 and Rs 103,000, respectively.

Weight comparison

The total effect weights represent the contribution of each input parameter to the output. These weights were calculated based on the weights of the input and output layers.

Table 2: Parameter weights of individual dataset

Parameter	Weights	
	Kidelpitiya	Meepe
Extent	0.1687	0.0265
Shape	0.1251	0.0302
Accessibility	0.0590	0.1913
Distance from	0.2177	0.1623
Number of access	0.1693	0.1690
Road frontage	0.0789	0.0835
Nature	0.0122	0.1000
Price per perch of	0.1692	0.2372

After training and validating the model using the individual datasets, the model was then trained using all data points from the larger dataset (Meepe land) and validated using all data points from the smaller dataset (Kidelpitiya land) as the test dataset.

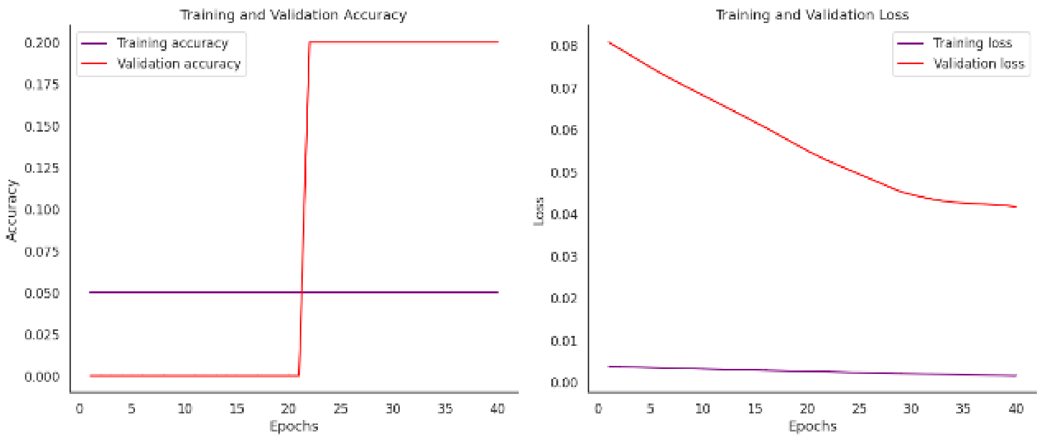

Figure 5: Training curve and validation curve of Meepe (Complete dataset)

Table 3: Evaluation matrix of Kidelpitiya (test dataset)

Error Matrices	**Kidelpitiya land (Test data)**
MAE	0.17541
MSE	0.06005
RMSE	0.24505

The maximum and minimum differences between the predicted and actual values for Kidelpitiya land were Rs 1,197,000 and Rs 9,000, respectively.

Actual vs. Predicted Land Values

The following table presents the actual and predicted land values along with the percentage difference for each lot:

Table 4: Actual and predicted land values

Lot	Actual Value (Rs)	Predicted Value (Rs)	Price difference Percentage
1	5,534,000	5,100,000	07.84%
2	4,700,000	4,766,000	01.40%
3	4,774,000	4,703,000	01.49%
4	4,991,000	4,487,000	10.10%
5	5,783,000	4,928,000	14.78%
6	4,752,000	4,503,000	05.24%
7	4,466,000	4,394,000	01.61%
8	4,437,000	4,428,000	00.20%
9	4,237,000	4,299,000	01.46%
10	4,086,000	4,309,000	05.46%
11	5,711,000	4,514,000	20.96%
12	4,973,000	4,419,000	11.14%
13	4,503,000	4,400,000	02.29%
14	4,400,000	4,261,000	03.16%
15	4,539,000	4,291000	05.46%
16	4,762,000	4,578000	03.86%
17	4,584,000	4,573000	00.24%
18	4,515,000	4,473,000	0.93%
19	4,410,000	4,452,000	0.95%
20	4,742,000	4,441,000	6.35%
21	4,796,000	4,498,000	6.21%
22	5,301,000	4,596,000	13.30%
23	5,194,000	4,820,000	7.20%
24	5,130,000	4,733,000	7.74%

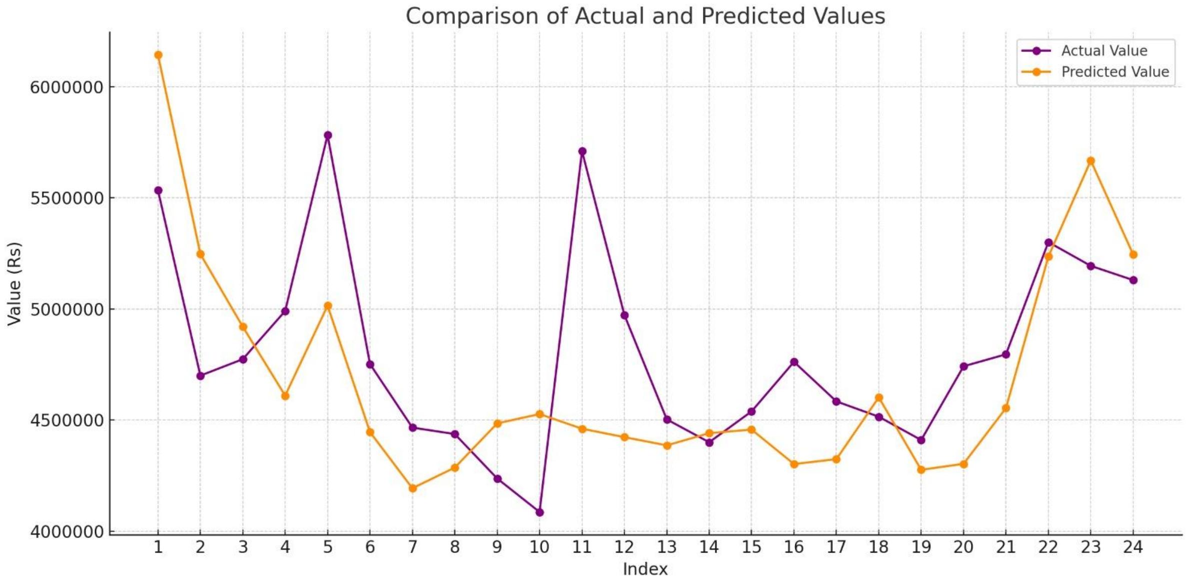

Figure 6: Actual and predicted land values Kidelpitiya (test dataset)

According to the Royal Institution of Chartered Surveyors (RICS) regulations, a tolerance value of 15% is acceptable for residential properties. The accuracy of the model was calculated as follows:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100\% \qquad (5)$$

$$= \frac{23}{24} \times 100\%$$

$$= 96\%$$

Property valuation is often a concern for both buyers and sellers, as they may perceive the valuation figure as either too high or too low. This is sometimes because different valuation methods yield different results, or because an estate agent or another valuer has provided a different estimate. Valuation is inherently a professional judgment, and differences between valuations do not necessarily indicate any misconduct or error by either party.

Traditional valuation methods are often subjective, relying heavily on the valuer's personal experience, intuition, and judgment. Expert appraisers or valuers may provide accurate assessments for a particular piece of land, but their valuations can vary due to the subjective nature of their methods. In contrast, the Artificial Neural Network (ANN) model used in this study treats all data as numerical values, seeking to establish a mathematical relationship between the inputs and outputs. This approach reduces the subjectivity inherent in human valuation.

However, some indirect factors can significantly affect land prices but may not be fully captured by the ANN model. For example, if a property is located near a landfill or a flood-prone area, its value may decrease substantially. Such contextual factors are challenging for a neural network to identify unless explicitly included in the dataset.

Furthermore, during periods of temporary market fluctuations (e.g., economic crises), residential land values may show resistance to change. This resistance occurs because residential lands are not typically seen as income-generating assets. The ANN model may not fully account for these nuances, highlighting a potential limitation in relying solely on numerical data for property valuation.

Conclusion

The application of an Artificial Neural Network (ANN) in this study resulted in highly accurate land value predictions, with a Mean Absolute Error (MAE) of 0.17541, and a Mean Squared Error (MSE) of 0.06005 during the validation process. The model achieved an accuracy level of 96%, consistent with the Royal Institution of Chartered Surveyors (RICS) property regulation tolerance value of 15%. In Sri Lanka, 10% tolerance value used in common factories in common practice. These results demonstrate that the selected parameters significantly impact land value prediction.

When comparing both datasets, it was evident that the larger Meepe dataset provided lower MAE and MSE values than the smaller Kidelpitiya dataset, indicating that having more data points improves the model's accuracy. As the model learns from a more extensive dataset, it captures more patterns, leading to better predictive performance. However, some variation in the weights of different datasets suggests that factors influencing land value may not be uniform across different regions.

Overall, the research represents a significant advancement in using machine learning techniques for real estate appraisal. The ANN model offers a reliable and efficient method for estimating residential land values, reducing the subjectivity inherent in traditional valuation methods, and enhancing decision-making processes in real estate markets

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