Received: May 22, 2024. Revised: June 26, 2024.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Real Estate Tax Prediction Using Hybrid Deep Learning Models

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Abstract: Future Real estate tax assessment and evaluation systems play a significant role in supporting public services and digital economy transformation. To automate and integrate complicated tax procedures, an intelligent taxation model is required. This research develops an automated hybrid deep learning neural network by integrating a multi-layer perceptron (MLP), bidirectional long short-term memory neural network (BiLSTM) and attention mechanism (AM) model which is limited for non-stationary, non-linearity real estate data offering superiority, interpretability, and dependability. The model has low error rates and great accuracy. The automated taxation model will enhance real estate tax inspection offices' efficiency by allowing for precise future tax base assessments and values. Deep learning neural network (DLNN) approaches can improve real estate price estimates and lead to more accurate tax assessments. The suggested model outperforms other benchmark price predictors (93%-98%) across many datasets and can be used for real estate taxation and inspection offices. The approach is useful for automated real estate price prediction and taxation applications. This research study proposes a revolutionary strategy that employs a hybrid deep learning neural network DLNN and challenges the conventional approaches to real estate tax base assessment future trends.

Keywords: Real estate tax assessment, Real estate price prediction, Attention mechanism, Bidirectional long short-term memory neural network, Deep learning.

1. Introduction

Assessing future real estate prices as a tax base assessment measure is a crucial supporting strategy for real estate tax evaluation and management reform for the economic expansion of any country and efficient public services funding. When automated tax base assessment is used, real estate developers' tax behavior may be continuously regulated, helping to guarantee that real estate taxes adhere to specific norms and enhancing tax credibility. Furthermore, conducting complex processes like field surveys, market research, and data collection might be time-consuming during the assessment. As the digital economy and transformation grows, the strain on estimators increases, leading to increased inaccuracy and decreased evaluation efficiency. Artificial intelligence (AI) and deep learning neural network (DLNN) models are used in predicting financial applications such as stock price [1] and real estate price prediction. Future real estate price tax base assessment is utilized to guarantee the objectivity and consistency of future trends in real estate pricing and the government should establish an automated, accurate, reputable, scientifically rigorous, fair, and unbiased future real estate price tax base assessment to levy and collect real estate taxes. Furthermore, real estate tax assessments are linked to the national economy and economic specialists, as they rely on previous historical data from each district tax office to value and estimate real estate prices. Real estate value prediction enables and supports governments, individuals, and corporations to construct efficient financial strategies, which leads to increased revenue for government projects and infrastructures. Expected future national real estate values affect real estate tax valuations. Automated and early estimation of real estate pricing helps owners, purchasers, developers, and governments make informed decisions and regulations. [2] Focus on real estate price prediction literature in finance, economy, and business studies. To accurately anticipate real estate values, it's important to consider the complexities of several predictor components [3, 4]. Machine learning (ML) has helped enhance decision-making in various fields, including predicting real estate market prices [5]. Real estate price prediction models based on real-world datasets were inspired by the success of machine learning approaches in other industries. Artificial neural networks (ANNs) are widely used in various ML applications, such as regression, classification, and language translation. Training noisy, nonlinear, and non-stationary time series datasets using ANN is challenging because the time component provides additional knowledge, but it also makes time series problems more complex to solve than many other prediction tasks in addition to substantial training time, implementation costs, lower efficiency and accuracy of utilized ANN. A popular and effective alternative is DLNN, which learns through a hierarchical approach. The dataset's strength, quality, and hyperparameter optimization significantly affect DLNN performance. While large datasets improve ML and DLNN performance, real-world scenarios may still require smaller datasets. Although commonly utilized for price prediction, DLNN's applicability in real estate applications is limited because of the difficulty of acquiring large datasets and the impact of small datasets on training and prediction performance. Real estate price prediction is a challenging time series problem due to multi-noise, nonlinearity, non-stationarity, and chaos [6]. Nonetheless, because of its importance, future real estate price prediction continues to garner more interest from scholars and investors. This paper conducts exhaustive research and experimentation in time series deep learning neural network techniques and concludes that integrating the multi-layer perceptron (MLP), bidirectional long short-term memory (BiLSTM), and attention mechanism (AM) (MLP-BiLSTM-AM) is the most efficient method to enhance the prediction accuracy of future real-estate prices. This research demonstrates the effectiveness of the MLP-BiLSTM-AM model on small, high-dimensional, nonlinear, and non-stationary real estate datasets in real estate tax district office that is made up of some temporal and non-temporal numerical and categorical features for the real estate tax valuation process. To do this, real datasets from Kaggle and data. world, and different sources of real estate dataset repository, four cities in different countries; Shanghai-China, Beijing-China, Shenzhen-China, Turkey, Busan-South Korea, Taiwan, Hefei-China, and Boston-USA, with different feature structures and dataset sizes are used to validate our proposed models. To validate and evaluate the proposed model, its performance is compared to the state-of-the-art and, GA-LSTM in Shenzhen-China [7], VAR for Busan-South Korea [8], CNN in Taiwan [9], LGBM in Beijing-China [10], and, these models validated with the same datasets. In addition, the number of hyperparameters and trainable parameters associated with the number of layers and neurons is the same for each model to decide which model performs effectively and efficiently. As a result, the performance of the MLP-BiLSTM-AM model in terms of real estate price prediction is compared to state-of-the-art models utilizing evaluation metrics and performance indicators for normalized root mean squared error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) evaluation metrics. The MLP-BiLSTM-AM model created in this work is efficient and effective for applications that anticipate real estate prices when each real estate unit's price is defined by small, nonlinear, and nonstationary datasets. As time series sequences increase, information loss will occur, making predicting less accurate. The Attention Mechanism (AM) could help address this issue [11]. In addition, AM has been effective in natural language processing, picture identification, and time series forecasting, [12] utilized better AM to predict energy consumption and weather. Furthermore, [13] used an AM-based model to handle picture-captioning jobs. Also, [14] proposed an AM-based healthcare prediction model. The research mentioned above has made significant progress in their fields, yet they also have limitations. For example, deep learning neural network models often include several neural network layers, which may not be appropriate for different types of real problems. The suggested model addresses the drawbacks by creating a hybrid model that utilizes the strength of each type of deep learning neural network. MLP's ability to handle input in parallel allows for faster feature transformation and gradient descent compared to other algorithms such as ARIMA, CNN, and other models. BiLSTM uses gate control and bidirectional transmission to recall or forget input and integrate temporal aspects. This work proposes a new hybrid deep learning model that combines MLP, BiLSTM, and AM, to address deficiencies in existing models. MLP is used to quickly modify the feature space and reach algorithmic convergence. BiLSTM extracts temporal features from real estate time series data. For AM that increase the weights of critical information in deep neural networks, resulting in more effective reasoning. The main contributions of this paper are briefly summarized as follows:

- We proposed an integrated model of deep learning neural network MLP-BiLSTM-AM that produces the best performance and accuracy of the real estate price prediction model for accurate real estate tax assessment.

- The hybrid combination of the three deep learning neural network structures; MLP, BiLSTM, and AM harness the strength points of each model as multi-layer perceptrons (MLP) used for fast feature transformation and gradient descent, a bidirectional long short-term memory neural network (BiLSTM) utilized for extracting temporal features from real estate price time series dataset, and finally, an attention mechanism (AM) used to prioritize critical temporal information through assigning higher weights and resulted in high price prediction accuracy in all datasets.

The performance of the proposed optimized MLP-BiLSTM-AM outperforms the state-of-the-art and traditional models; GA-LSTM in Shenzhen-China [7], VAR for Busan-South Korea [8], CNN in Taiwan [9], LGBM in Beijing-China [10]. Therefore, the hybrid model MLP-BiLSTM-AM for DLNN is anticipated to enhance the DLNN model's prediction using real datasets for real estate price prediction problems and real estate tax assessment. The rest of this paper is organized as follows: Section 2 reviews the related work of time series real estate price prediction models. Section 3 introduces the proposed methodology and architecture of a deep neural network MLP-BILSTM-AM for the real estate price prediction approach. Section 4 discusses the experimental design and its outcomes, analysis, and results. Finally, section 5 presents the conclusion and future work.

2. Related work

Large fluctuations in the real estate market can have a significant negative influence on the public economy. Accurate real estate tax base price prediction can prevent real estate tax collapses and guide the real estate taxation authority to operate smoothly, laying a solid foundation for the economy's long-term health. As a result, the study of intrinsic value and real estate price prediction has received increasing interest from both researchers and practitioners, and several outcomes have been achieved. The real estate tax base price is volatile and irregular; with complicated real estate data from the field survey that includes small volume, inaccurate, non-linearity, and non-stationary. Time series real estate prices have been predicted using many techniques, including conventional statistical methods, machine learning, deep learning, and hybrid models. Conventional approaches, such as autoregressive-moving-average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH), have lower prediction accuracy on non-stationary data [15], in addition, they assume that conditional variance innovations follow a normal distribution. This assumption is not always true in financial data. Statistical models include vector Autoregressive Models (VAR) [16] in modeling time series and it is critical to ensure the stationarity of the data to avoid erroneous regression by differentiating a time series that can transform non-stationary sequences. In addition, [8] used vector autoregression (VAR) for the prediction of rental real estate pricing in the city of Busan, South Korea, despite that the VAR model offers advantages over ARIMA by incorporating several time series in a single model and VAR prediction is widely used in economic and financial studies due to its efficiency and predictability. One of the primary disadvantages of utilizing VAR for predicting is the need for a significant amount of data and precise lag duration selection. If you have too few observations or too many lags, you may overfit the model and get incorrect predictions. Furthermore, the autoregressive integrated moving average (ARIMA) in [17] is used for house price prediction. In addition, [18] used the ARMA model in real estate price prediction, the main disadvantage of the ARMA and ARIMA models; they are linear models and are limiting and difficult to predict time series due to their inability to handle nonlinear interactions or complex dynamics, and their parametric assumptions, which can impact model estimate and prediction effectiveness, make them unsuitable for short or long periods. In addition, Machine learning algorithms are commonly employed for real estate prediction due to their ability to handle nonlinear data. Machine learning techniques like Random Forest (RF) and Support Vector Machines (SVM) may effectively identify nonlinear correlations between real estate price and their influencing features. However, these methods heavily rely on sample selection during model generation, making them inflexible and prone to errors. As a result, the prediction accuracy struggles to meet prediction standards. In addition, the regression models, such as logistic regression models (LR) [19], Although these models are employed as time series predictors, are unable to memorize past data or adjust to sudden shifts in trend, which is considered drawbacks of using machine learning in time series prediction problems. Furthermore, [20] used the decision trees model (DT), nevertheless, DT learners can produce too complicated trees that do not generalize the time series data adequately, resulting in data overfitting. Also, support vector machines (SVM) are used in

[21], however, the SVM method is not appropriate for long-time dependences datasets, and when the dataset contains nonstationary SVM performs poorly. Various researchers employ machine learning models such as random forest (RF) [22]. In [23] used RF in real estate price prediction, however, the random forest's key restriction is that a huge number of trees might render the process too sluggish and inefficient for real estate time-series predictions. Random Forests are difficult to interpret and computationally costly on huge datasets, in addition, RF works similarly to a black box algorithm, with minimal control over what the model accomplishes in addition, RF needs for manual creation of lag and seasonality variables. Deep learning neural network models DLNNs offer more powerful learning and self-adaptive capabilities than typical machine models, allowing them to perform better in real estate tax base price analysis. Deep learning neural network (DLNN) algorithms have demonstrated advanced performance in classification and regression problems, specifically, in time series real estate prices prediction on benchmarked datasets. Furthermore, hybrid DLNN outperformed alternative machine learning methods despite the complexity, nonlinearity, multidimensionality, and data scarcity. Deep learning models, including artificial neural networks (ANN), multi-layer perceptron (MLP), convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM) neural network, and bidirectional long short-term memory (BiLSTM), have gained popularity due to advancements in computer processing power and the ability to learn complex nonlinear mapping and self-adaptation for various statistical distributions [24]. Conventional RNNs have vanishing and exploding gradient issues, which might limit their capacity to capture long-term dependencies. The long short-term memory (LSTM) neural network excels at handling extended input sequences and non-linear data. It is commonly used in time series prediction due to its superior memory capacity and gate structure, unlike other recurrent neural networks that can only retain short sequences [25]. Bi-directional long short-term memory (BiLSTM) is an extension of unidirectional LSTM that can learn bi-directional time series features, improving model prediction accuracy. Despite LSTMs advantages and their usefulness in numerous fields, including NLP and speech recognition, they suffer from some drawbacks such as; LSTMs are computationally more complex than other neural network architectures, causing slower training times and potentially requiring more resources. LSTMs are prone to overfitting when there is inadequate training data. Finding the proper set of hyperparameters for a particular problem can be a difficult and time-consuming task, **limited interpretability,** makes it difficult to understand how they reached a given outcome. Finally, long training times: training deep LSTM models on large datasets can take time and may need the use of powerful hardware, such as GPUs or TPUs. Contrasting the prediction performances of LSTM, RNN, and CNN models of three layered networks they discovered that an LSTM-based performed better than previous traditional models. Different models demonstrate their respective merits such as using CNN and LSTM for time series data. As in [9] used CNN in real estate price prediction in Taiwan, to assess the effectiveness of house price prediction techniques based on the deep learning algorithms; CNN. According to experimental findings, CNN has the best influence on prediction when housing features are included, but CNN are intended to handle data with a grid-like topology, such as images, and are unsuitable for handling time series data, which has a sequential structure. CNNs can be used to analyze time series data by framing it as images, however, this approach is not extensively used and is often less effective than using a model particularly created for time series data such as LSTM's and its variation models. In [26] LSTM was able to anticipate real estate prices. In addition, hybrid models are necessary to address complex prediction situations with numerous features. Furthermore, deep learning neural network (DLNN) and hybrid algorithms have demonstrated advanced performance in predicting time series real estate prices such as in [27] used hybrid models in a single network improved the predictability of financial time series problems. In [10] making predictions in Beijing housing values with complicated features, this study compares and evaluates deep learning models using the LightGBM model, furthermore, LGBM is computationally expensive and susceptible to overfitting. In addition, [28] coupled deep belief networks (DBNs) with MLP, and [29] utilized CNN and LSTM to gain better prediction performance. In addition, Bidirectional recurrent neural networks (BRNN) were created by extending recurrent neural networks (RNN). The work demonstrated that BRNN may be trained up to a predetermined future frame without the restriction of user input information [30]. Although BRNNs and Bi-LSTMs often employ various topologies and activation functions, they are both capable of accurately predicting real-world time series data [31]. Nevertheless, in [32] studied the use of a hybrid ARIMA and neural network model for time series prediction, because there are linear and nonlinear correlation structures between the observations in these series, and the results showed

that the hybrid model created for this study that neither ARIMA nor ANN is appropriate for all real-time series problems. As a result, they claim that the suggested hybrid model may be a helpful tool for time series estimation [33]. [34] Offer an ensemble learning strategy for predicting housing prices that combines the LSTM for predicting real estate price index with a boosting tree model. In addition, [7] LSTM incorporating a modified GA is proposed for predicting the future trend and fluctuation of real estate prices of cities in China, however, the proposed model has some limitations. The GA-LSTM technique produces good results, but is time-consuming; therefore, the model's efficiency should be enhanced. In [35] compared ARIMA, LSTM, and hybrid models and employed time series analysis and the results revealed that the hybrid model produced the best performance among separate models in Turkey, in addition, this small dataset can lead to weaker model performance. In [36] used real estate price prediction system based on temporal and spatial features and lightweight deep learning model in Taiwan. This can be minimized by employing feature selection or dimensionality reduction techniques like principal component analysis and autoencoders, and they can be sensitive to hyperparameters such as the number of hidden units, learning rate, and activation function, all of which can affect the network's convergence and accuracy. Deep Learning systems, in particular, have shown excellent outcomes in short and long-term time-series predictions. As a result, these strategies are ideal for predicting real estate tax prediction systems. The current work employs a MLP-BiLSTM-AM hybrid deep learning model to estimate real estate price values as a tax base assessment.

3. The proposed methodology

This section introduces the hybrid deep learning neural network model MLP-BiLSTM-AM by integrating multilayer perceptron (MLP) with bidirectional long short-term memory (BiLSTM) with attention mechanism (AM) method for real estate price prediction problems with small, multidimensional, non-linear, and non-stationary time series datasets for the assessment of the real estate taxation system. MLP was used for rapid non-temporal feature transformation, then BiLSTM was used to extract temporal features from real estate price time series data; and an AM was used to prioritize crucial temporal information by assigning higher weights, resulting in high price prediction accuracy for each dataset of the four benchmarked datasets used in this study. Finally, build a hybrid deep neural network with the optimized architecture and hyperparameters to give the most accurate real estate price prediction models for real estate tax estimation and levying system. The proposed models are evaluated and validated against the state-of-the-art and conventional benchmarked method by the same real estate datasets.

3.1 Multi-layer perceptron (MLP)

The simplest MLP [37] has three layers: input, one or more hidden, and output. The input of each neuron in the previous layer is calculated by multiplying the output of the previous layer by the weight matrix and then adding the bias matrix. Nonlinear activation functions convey calculation results from each layer. The first step is to initialize the model's parameters, known as hyperparameters. The MLP model's major hyperparameters include learning rate, activation function, number of epochs, layers, neurons, and activation, loss, and optimization functions. The network's first layer is initialized with the normalized feature matrix X^* as shown in Eq. (1).

$$X_i* = \frac{\boldsymbol{Xi} - \mu}{\boldsymbol{\sigma}} \quad (1)$$

Where i indicates the index of the variables, μ and σ indicate the mean and standard deviation of the variables, respectively. The processing and the outcome of the MLP are shown in Eq. (2).

$$MLP = \varphi^o \left[\sum_{j=1}^{J} W_{pj}\, \varphi^h \left(\sum_{i=1}^{I} W_{Ji}\, X_i* + b_j^h\right) + b_p^o\right] \quad (2)$$

Where i, j, and p represent the input, hidden, and output layer neurons, respectively, $\varphi(.)$ is the activation function. J and I represent the indexes of input and hidden layer neurons, respectively. X_i* represents the normalized input feature matrix. W_{ji} is the weight matrix that connects the i^{th} neuron of the input layer to the j^{th} neuron of the hidden layer. W_{pj} is the weight matrix that connects the j^{th} neuron of the hidden layer to the p^{th} neuron of the output layer. b_j^h and b_p^o represent the biases matrix of hidden and output layers respectively, of the j^{th} neuron in the hidden layer and p^{th} neuron in the output layer.

3.2 Bi-directional long short term memory (BiLSTM)

RNN is an effective deep learning model for processing time series data due to its ability to present dynamic temporal aspects within its internal state. A vanishing gradient may occur as the information interval (specified length) increases due to

Received: May 22, 2024. Revised: June 26, 2024.

multiplication with the reciprocal of the tanh function and weight matrix. LSTM [25], an expanded variation of RNN, successfully addresses the vanishing gradient in standard RNNs. LSTM uses a gate control structure to determine whether input should be remembered or forgotten. It can also employ information from long-time sequences. The LSTM model stores features using memory cells and three gates; input gate, forget gate, and output gate which address the long-term feature problem. Fig. 1 shows the architecture of the LSTM unit.

The output of the cell is denoted as h_t, c_t is denoted as cell value memory, h_{t-1} represents the previous step of cell output. X_t is the input data at time t. Eqs. (3)-(8) describe the systematic process of the LSTM unit. The forget gate (f_t), bias (b^f), and weight matrices (W^f) and (B^f), are used to regulate historical data in memory cell states. The forget gate process is given in Eq. (3) as follows:

$$f_t = \sigma(W^f X_t + B^f h_{t-1} + b^f) \tag{3}$$

the forget gate is responsible for determining whether the information from the previous step should be discarded or saved in the memory cell state, this is completed by the first sigmoid activation function (σ). The input gate (i_t), weight matrices (W^i and B^i,), sigmoid function (σ), and bias (b^i) are used to update the memory cell state based on the current input data. The input gate process is described in Eq. (4).

$$i_t = \sigma(W^i X_t + B^i h_{t-1} + b^i) \tag{4}$$

In Eq. (5), $\tilde{c}_t$ represents a candidate memory cell, b^c represents bias, and W^c , B^c represents the weight matrices, and tanh is a hyperbolic tangent activation function.

$$\tilde{c}_t = tanh(W^c X_t + B^c h_{t-1} + b^c) \tag{5}$$

The LSTM unit's last cell state value is denoted as c_{t-} in the current memory cell c_t as shown in Eq. (6).

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}t \tag{6}$$

Where $\odot$ describes the Hadamard product of the two matrices. The memory cell controls the input and output gate based on the state values of the last and candidate cells. Cell state serves as the memory of an LSTM. At each timestep the previous cell state (c_{t-1}) combines with the f_t forget gate to decide which information is to be carried forward which in turn joins with the input gate i_t and candidate cell state $\tilde{c}_t$ to generate the new and updated memory cell state c_t. Then, the output gate process is shown in Eq. (7) as follows:

$$o_t = \sigma(W^o X_t + B^o h_{t-1} + b^o) \tag{7}$$

Where o_t is the output gate, the weight and bias matrices are denoted as W^o, $B^{o,}$ and b^o respectively. Finally, the output of the LSTM cell state obtained is passed through a hyperbolic function called tanh so that the cell state values are between -1 and 1.

The LSTM unit output is denoted as h_t as given in Eq. (8).

$$h_t = o_t \odot tanh(c_t) \tag{8}$$

The LSTM model stores and updates long-term information using memory cells and control gates.

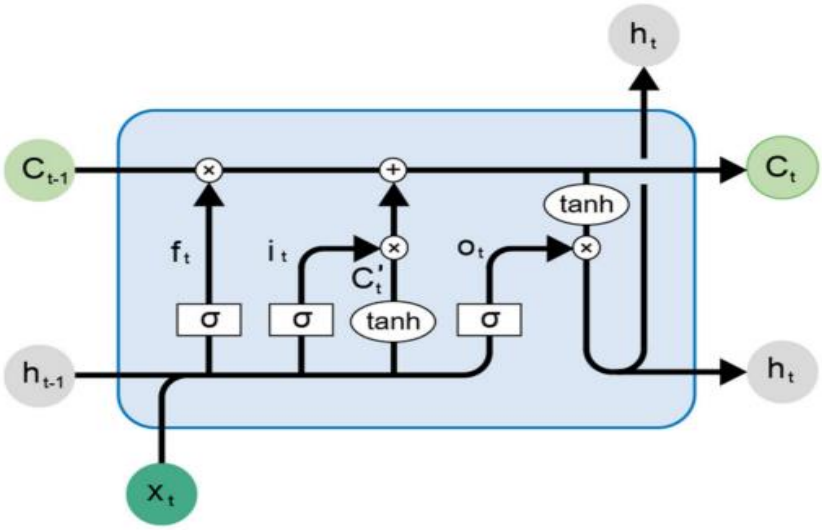

Figure. 1 The architecture of the long short-term memory (LSTM) model

 DOI: 10.22266/ijies2024.1031.19

The LSTM model controls output dimension through weight matrix adjustments based on internal parameters. The BiLSTM model combines two LSTMs and applies sequence learning to tokens based on both past and future content. The BiLSTM model processes data in two directions: left to right and right to left. The forwarding process uses the hidden unit function $\overrightarrow{h}$ at the hidden forward layer, while the reverse process uses the preceding hidden state h_{t-1} at each time step t. Hidden backward layers are utilized by the hidden unit function $\overleftarrow{h}$ and the future hidden state $\overleftarrow{h}_{t+1}$. Concatenate $\overleftarrow{h}_t$ and $\overrightarrow{h}_t$ to form a long vector that represents the forward and backward process. The predicted real estate price value is obtained using the combined outputs.

3.3 Attention mechanism (AM)

AM has become a significant topic in deep learning. This technique assigns higher weights to important temporal information, allowing the neural network to prioritize critical information. Eqs. (9)-(11) describe how AM is implemented as follows: The attention score at time t is given in Eq. (9).

$$S^t = F\,(X^t, C^{t-1}, \gamma^{t-1}) \tag{9}$$

In Eq. (9) S^t represents the attention score at time t, which is controlled by the input variable X^t, previous state $C^{t-1,}$ and γ^{t-1} previous attention weights.

The i^{th} instance of the attention weight process γ_i^t is given in Eq. (10).

$$\gamma_i^t = e^{S_i^t} / \sum_{i=1}^{I} e^{S_i^t} \tag{10}$$

whereas i and I represent the index and number of attention scores at a time t respectively, S_i^t represents the i^{th} instance of the attention score at time t.

In Eq. (11), at time t, F_i^t is the i^{th} weighted feature defined by the attention weight γ_i^t and the input variable X_i^t.

$$F_i^t = \gamma_i^t\, X_i^t \tag{11}$$

Finally, the future real estate prediction price is performed using the training parameters and hyperparameters. Repeating the stated MLP-BiLSTM-AM technique over the parameters and tuned hyperparameter for all four datasets. The proposed framework consists of three main phases: Building the multilayer perceptron MLP, building a bi-directional long short-term memory deep neural network BiLSTM with attention mechanism AM method MLP-BiLSTM-AM, and finally the process of future real state tax assessment.

3.4 Real estate tax base price prediction using MLP-BiLSTM-AM

This paper offers a hybrid deep learning model that combines MLP, BiLSTM, and AM to successfully extract relevant information from real estate data and avoid limitations of existing models. This work combines MLP and BiLSTM to accelerate feature transformation and convergence. Fig. 2 depicts an overview framework of the suggested model, which is explained below. A dataset that contains monthly historical prices of real estate. After preprocessing and analyzing the technical indicators. Fig. 2 illustrates the study's deep learning structure, which combines MLP, BiLSTM, and AM. MLP accelerates the change of the feature space, resulting in quick algorithmic convergence. BiLSTM is effective in extracting temporal features from real estate time series data. Combining MLP and BiLSTM allows for successful extraction of temporal features from real estate data using rapid gradient descent. Proper temporal feature extraction improves predicting accuracy. AM is integrated with MLP and BiLSTM neural networks to prioritize temporal input with greater weights. As a result, different weights can be allocated to distinct input sequences, increasing the prediction accuracy even further. AM was utilized to improve predicting accuracy by prioritizing important temporal information. Finally, the predicted results were displayed, the process of real state tax assessment as illustrated in Fig. 2.

4. Experimental details and results

This section is organized as follows: Section 4.1 introduces the description of the datasets. Section 4.2 presents the evaluation metrics of the proposed models. Section 4.3 presents the experimental system setting. Section 4.4 highlights the experimental results and findings.

4.1 Datasets

This paper makes use of the real estate price dataset from Kaggle, Data.world, and Lianjia valuable real estate transaction websites. In this context, four real estate pricing datasets are; Shenzhen-China, Busan-South Korea, Taiwan, and Beijing-China. Each dataset has a different size and exploratory features including monthly temporal price features. In Shenzhen dataset consists of eight features containing relevant and time series monthly price data from 2010 to 2017 for 83 months.

Figure. 2 The proposed hybrid deep learning neural network MLP-BiLSTM-AM framework for real estate price prediction for real estate tax assessment

In Busan, a time series pricing real estate dataset of 167 months from 2006 to 2019 was used. In addition, in Taiwan, the monthly pricing real estate dataset from 2013 to 2018 containing 60 months was used. Furthermore, in Beijing, the time series real estate dataset contains real estate price data from 2011 to 2017 for 92 months, and the dataset involved 18 temporal and non-temporal features. To improve the performance and generalization of artificial neural networks (ANN), good-quality datasets were collected, cleaned, and preprocessed. This included data imputation, outlier detection, deletion of irrelevant features, normalization, and feature scaling, one-hot encoding for categorical features. The datasets were randomly divided into 80% for training and 20% for validation.

4.2 Model evaluation metrics

Verifying and validating a deep learning neural network (DLNN) model requires appropriate evaluation indicators. This study uses three indicators for comparison: root mean squared error (RMSE) [38], mean absolute error (MAE), and coefficient of determination score (R^2). Lower RMSE, and MAE, and, as well as higher R^2, improve prediction accuracy. These metrics are often used in real estate appraisal research [39]. The comprehensive model evaluation technique uses three indicators and takes into account their respective emphasis. Eqs. (12)-(14) provide specific calculations for each indication.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - yi')\ 2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - yi'| \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - yi')2}{\sum_{i=1}^{n}(yi - y\hat{}i)2} \tag{14}$$

R^2 measures the degree of variation, quantifies the link between predicted and desired price and fits on a scale of 0–1 percent as in Eq. (14), where i and n indicate the index and number of predicted days, months, quarters, or yearly respectively, according to problem periods, and yi and yi' indicate the true values and predicted values, respectively. y^ indicates the mean value of y. The RMSE and MAE evaluation metrics are applied across the normalized projected and actual price labels since they are both sensitive to normalization scaling.

4.3 Experimental system setting

The proposed hybrid deep neural network model MLP-BiLSTM-AM was built using Tensorflow, and various third-party Python libraries are used such as Pandas [40] for data structure, and Scikit-learn for evaluation metrics, scaling, normalization, and standardization for feature values and determination and model selection. In addition, the proposed MLP network contains two to five layers and 32 to 512 neurons, the neural attention layer dimension is set to 64, ReLU activation function was used for all the hidden layers and linear for the output layer. In addition, we set the dropout to 0.2, the learning rate to 0.001, and the sequence length is set to from 25 to 50. Adam as the optimization function epochs is set to 200; the batch size was set to 32. The remaining best hyperparameters are set by default values as shown in Table 1. The hardware configuration was as follows: Intel(R) Core (TM) i5-6200U 2.70 GHz CPU, 12 GB RAM, with T4-GPU, and Win10 pro-OS. For all four datasets, 80% of each class is used as a training set, and the rest 20%, as the test set. The four datasets are fed into the proposed MLP-BiLSTM-AM model to obtain the best real estate prediction models with minimum RMSE, MAE, and maximum R2 in Eqs. (12)-(14).

4.4 Results and analysis

The Analysis of the quantitative performance measures, namely; RMSE, MAE, and R2 in the training phase, each dataset from the four datasets preprocessed, scaled, normalized, and fed into the MLP-BiLSTM-AM model. We compared four of the Selected datasets of the proposed hybrid MLP-BiLSTM-AM model with conventional techniques; Long short-term memory integrated with genetic algorithm (GA-LSTM) [7], vector autoregression (VAR) [8], Convolutional neural network (CNN) [9], in addition, light gradient boosting model (LGBM) [10], Performance indicators; RMSE, MAE, and R2 evaluation metrics are used as performance measure metrics in comparison for proposed hybrid MLP-BiLSTM-AM versus the [7-10]. From Table 2, we can observe that the proposed model outperforms the conventional techniques on four datasets with a significant ratio. This proves that the hybrid MLP-BiLSTM-AM deep neural networks method is better than other traditional techniques. For real estate price prediction in Shenzhen [7], our proposed hybrid DLNN model outperformed the GA-LSTM model in all evaluation metrics. For RMSE minimized from 0.413 to 0.115 and for MAE the error was reduced from 0.405 to 0.345 in our proposed model, and the R^2 coefficient of determination enhanced from 0.753

Table 1. The optimum network architecture of the proposed MLP-BiLSTM-AM for the four selected datasets

Parameters	Descriptions	Value
Attention-dim	Neural attention layers dimension.	64
Lay-Num	Number of layers	5
Time-Pred	Time of data used to make the prediction	4
Neurons-size	The number of neuron units in each bi-lstm layer	128
Epoch	Displaying the total number of computations that can be done both forward and backward.	200
Batch-size	The amount of data transferred to the train model	32
Learning-rate	Updating of the network weights by the loss gradient.	0.001
optimizer	Parameter and training tuning to reduce the loss of function.	Adam
Dropout	Training batches have the potential to significantly decrease the process of learning to adapt.	0.2
Sequence length	For each data point in the training and test sets, we create a sequence length by sliding a window through the data.	25-50
Activation Function	The activation function introduces non-linearity into the output of a neuron.	ReLU
Dense size	The number of neuron units in the dense layer	32
Loss function	The function calculates the error and minimizes it during the model training process to improve accuracy.	mse

Table 2. Performance of the state-of-the-art methods and the proposed method for the selected real estate datasets in terms of, RMSE, MAE, and R^2 evaluation metrics

Source	Region	RMSE	MAE	R^2
GA-LSTM [7] vs MLP-BiLSTM-AM	Shenzhen-China	0.413 vs **0.115**	0.405 vs **0.345**	0.753 vs **0.924**
VAR [8] vs MLP-BiLSTM-AM	Busan-South Korea	0.054 vs **0.020**	0.154 vs **0.102**	0.942 vs **0.964**
CNN [9] vs MLP-BiLSTM-AM	Taiwan	0.128 vs **0.089**	0.254 vs **0.163**	0.945 vs **0.978**
LGBM [10] vs MLP-BiLSTM-AM	Beijing-China	0.309 vs **0.048**	0.252 vs **0.185**	0.810 vs **0.960**

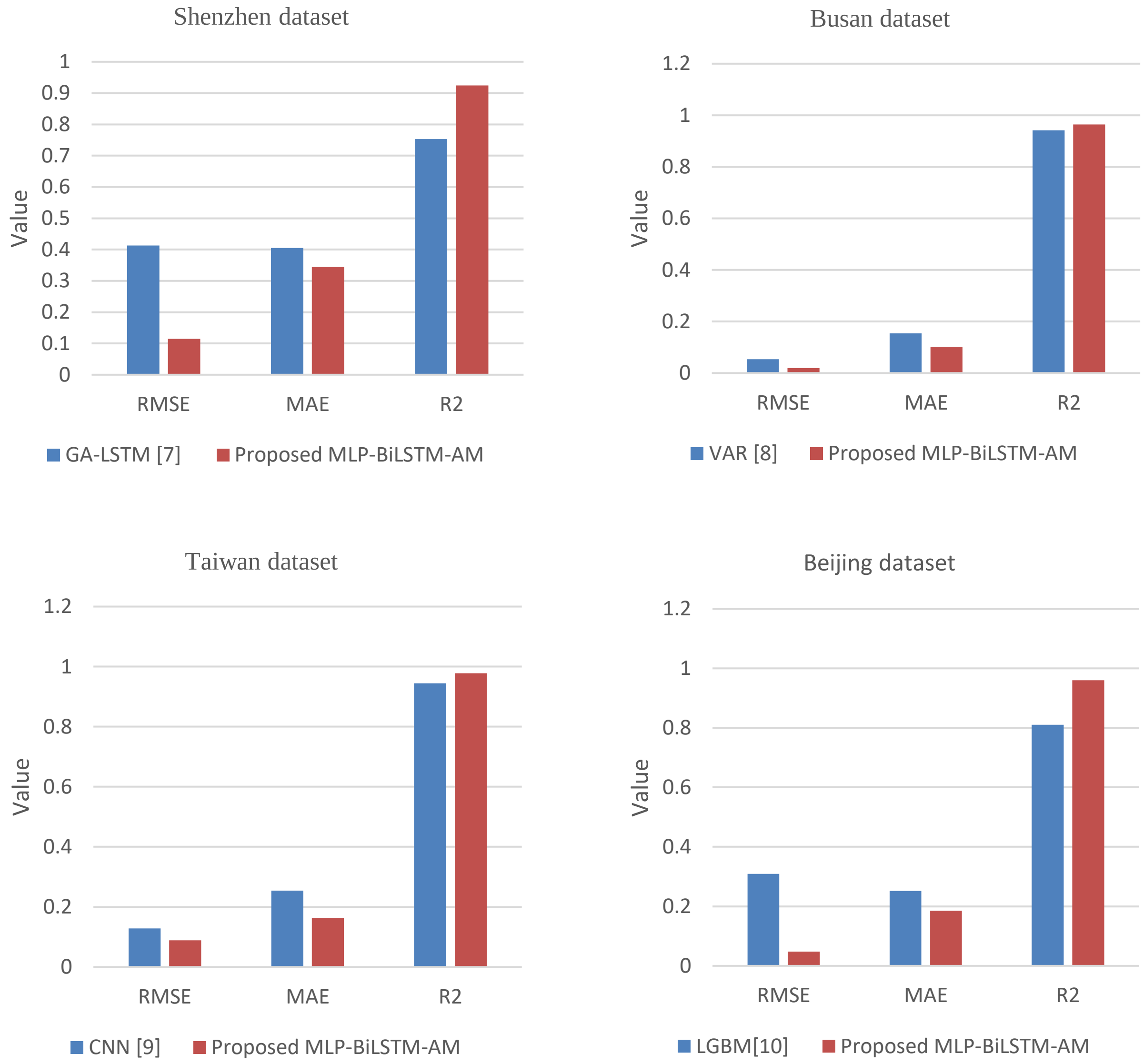

Figure. 3 Performance metrics (RMSE, MAE, and R2) comparison between the proposed approach MLP-BiLSTM-AM and conventional approaches using real datasets

to 0.924, which is a significantly good value for R^2, the GA-LSTM technique, despite its effectiveness, is time-consuming and requires improvement in efficiency, especially with a smaller dataset, to improve the model performance. In [8], our suggested approach outperformed the VAR model for predicting real estate prices in Busan by 2% in R^2 from 0.942 to 0.964, our proposed hybrid DLNN model lowered RMSE from 0.054 to 0.020 and MAE from 0.154 to 0.102. VAR for prediction has disadvantages like large data requirements and lag length selection, which can lead to overfitting and inaccurate predictions, and may not account for structural changes. For Taiwan [9] real estate price prediction our proposed framework outperformed CNN in all performance indicators; for RMSE reduced from 0.128 to 0.089, MAE minimized from 0.254 to 0.163, and R^2 improved by approximately 3% from 0.945 to 0.978, furthermore, CNNs are ideal for grid-like data like images, but not for sequential time series data. While they can analyze time series data as images, this approach is less effective. In addition, the proposed framework outperformed the LGBM [10], the LGBM is computationally expensive and susceptible to overfitting, and our proposed model surpassed the LGBM model in RMSE evaluation metric minimized from 0.309 to 0.048, in MAE the value reduced from 0.252 to 0.185, and R^2 maximized from 0.810 to 0.960. The experimental findings show that the suggested deep learning neural network hybrid model's predictions are more accurate as shown in Fig. 3. The proposed model accurately predicts different real estate price indices and has a low likelihood of overfitting. To achieve real-time performance, the proposed approach needs to be made faster. Accuracy in price prediction is crucial in real estate, but balancing computing complexity and efficiency remains challenging. In the future, exploring alternate techniques to reduce system complexity.

5. Conclusion

This study introduces an effective approach to assessing future trends of real estate tax bases, utilizing the untapped power of deep learning neural networks to break new ground and explore new possibilities. We proposed a hybrid deep learning neural network model that combines multilayer perceptron (MLP), bidirectional long short-term memory neural network (BiLSTM), and attention mechanism (AM), to estimate the future trends of real estate prices in small, high-dimensional, nonlinear, and nonstationary time series datasets, which can then be used to estimate and levy future real estate taxes. The proposed framework achieves a high-accuracy real estate price prediction model. Extensive experimentations were conducted on four benchmark real estate datasets; Shenzhen, Busan, Taiwan, and Beijing, to validate and verify the efficiency and effectiveness of our proposed framework. The results obtained revealed that the proposed framework outperforms the conventional techniques and can be generalized to other time series real estate datasets. Our suggested approach improved accuracy in the R^2 assessment metric and achieved a minimum root mean squared error (RMSE) and mean absolute error (MAE) across all four datasets. Therefore, the proposed MLP-BiLSTM-AM provides a better prediction of real estate tax base price. From the results, it is concluded that the proposed model outperforms well in R^2 evaluation metrics than the GA-LSTM, VAR, CNN, and LGBM and achieves 0.924, 0.964, 0.978, and 0.960 respectively. The RMSE of MLP-BiLSTM-AM is minimized and is less when compared to the GA-LSTM, VAR, CNN, and LGBM of 0.115, 0.020, 0.089, and 0.048 respectively, and for MAE MLP-BiLSTM-AM is reduced and is less when compared to the GA-LSTM, VAR, CNN, and LGBM of 0.345, 0.102, 0.163, and 0.185 respectively. The proposed method has significant advantages: 1) the MLP-BiLSTM-AM hybrid model obtained high prediction accuracy for deep learning neural networks to gain the strength of the integration of all models other than using each model separately. 2) The proposed model achieves high performance in real estate price prediction problems when compared with other conventional approaches with feasible running time, making it ideal for a variety of applications. 3) The time series real estate pricing dataset is managed effectively by the suggested MLP-BiLSTM-AM model with small high-dimensional and nonlinear real estate datasets. Although the suggested model achieved good predicting accuracy, it still has certain drawbacks; the deep learning model's parameters were determined through trial runs and the computational performance has to be more efficient. In the future, additional studies may develop a more reliable and accurate real estate price appraisal model by using additional and different feature datasets. Also, automating the hyperparameter selection procedure. In addition, generalized our proposed hybrid model to other real estate price datasets for real estate tax assessment in different regions. Future studies should use different attention mechanisms to analyze the internal structure of AM. Future studies will incorporate numerical and textual data, as well as natural language processing techniques, to enhance the model's prediction performance. Additionally, we will investigate combining the proposed methodologies with additional types of deep-learning neural networks.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Amal R. Saleh, Motaz A. Elsaban; methodology, Amal R. Saleh, Motaz A. Elsaban, Mohamed M. Saleh; software, Amal R. Saleh; validation, Motaz A. Elsaban, Mohamed M. Saleh, Hisham M. AbdelSalam, formal analysis, Amal R. Saleh, Motaz A. Elsaban, Mohamed M. Saleh, data curation, Amal R. Saleh; writing-original draft preparation, Amal R. Saleh, Motaz A. Elsaban; writing— review and editing, Amal R. Saleh, Motaz A. Elsaban; Mohamed M. Saleh; visualization, Amal R. Saleh; supervision, Mohamed M. Saleh, Hisham M. AbdelSalam.

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