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# Evaluating Machine Learning and Deep Learning Models for Housing Price Prediction: A Review

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**Abstract:** *In the world of the housing market, a dynamic and sensitive market, high dependence on machine/Deep learning (ML DL) for price prediction has been observed. This research indicates that certain machine learning and deep learning algorithms, including support vector machines, LSTM, RNN, decision trees, random forests, and linear regression, may detect both linear and nonlinear correlations in housing data. In this way, these models have become helpful to stakeholders like homeowners, investors, and urban planners for predicting the prices accurately and understanding the market trends. Model overfitting is still a challenge; feature selection and accuracy of the data still persist. In the future, research could be conducted on how to integrate many data, from real market trends to multimodal data such as property images in order to improve prediction accuracy. Further, hybrid models that combine the best of all in algorithms, as well as reinforcement learning and sophisticated optimization strategies, could also increase the ability and performance. Nonetheless, fairness and bias in automated systems have to be another part to take into consideration to assure an equitable result for all on behalf them. By raising these areas, housing price prediction models can grow sturdier, reliable and helpful for steering exact estate decisions, aiding the people and overall economy..*

**Keywords:** Housing price prediction, machine learning, deep learning, linear regression, decision trees, random forests, LSTM, RNN, real estate, data quality, hybrid models, ethical AI

## I. INTRODUCTION

The housing market among the first and most pervasive businesses to pique the interest of the general public was the real estate industry. Due to its constant evolution, it has been characterized as the ecosystem's least transparent industry. Much research in the last several years has analyzed the housing market using state-of-the-art ML models to determine the most important variables influencing prices and to forecast future price changes, all made possible by the proliferation of computational methods. Whether it's predicting the future of the market [1][2], popular neighborhoods, or the most in-demand construction types, these computerized models assist homeowners, builders, and businesses in making better-informed decisions and increasing their profits. They also provide a hand to city planners and administrators in arranging a city's physical and environmental features in a way that benefits the most people.

In recent years, ML has become a vital tool for estimating the worth of homes depending on their characteristics [3], independent of historical data, thanks to the increasing interest in Big Data. Several investigations into the matter demonstrated the efficacy of the ML strategy.

The aim of using historical data on home attributes (such location, number of bedrooms and baths, square footage, etc.) and their associated costs, a model to precisely predict a new home's cost precisely based on its attributes may be created [4]. ML advances have led to the development of several algorithms that can accurately forecast future real estate values.

This study's main goal is to employ these ML approaches to develop ML models that will be useful to users. Finding the perfect house with all the qualities a buyer needs is their first priority. Furthermore, when individuals look for these houses or real estate assets, they have a price in mind, and there is no guarantee that they will get the item at a reasonable cost without being overcharged.


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The primary objective of this work is to curate a variety of ML approaches into consumer-beneficial ML models. Finding the perfect house with all the amenities a buyer needs is their first priority [5]. Furthermore, there is no guarantee that they will receive the goods at a reasonable price or without being overcharged because individuals look for these homes and real estate properties with a certain price in mind.

## II. HOUSING PRICE PREDICTION: PROBLEM OVERVIEW

The basic description and asking price are sometimes displayed separately from the generic and standardized real estate features. These attributes may be readily compared over the whole spectrum of possible houses since they are given separately and in an organized manner. Property sellers may include all of the property's salient features in the description as each one has unique characteristics of its own, such as a particular view or washing machine kind. The range of property prices is of great importance to both buyers and sellers since it is a key indicator of the status of the economy [6]. This study will anticipate home values using explanatory factors that encompass a wide variety of residential housing features. The project's objective is to develop a regression model that, given its parameters, can reliably predict a home's price.

This section provides the details on how affecting the factors and challenges to predict the house price.

### A. Factors Affecting Housing Prices

- Two criteria are the cost of the land acquisition and the finished home. A type of real estate is commodity housing, where the cost of a home includes the land price, building costs, profit, and taxes.
- It is evident that Variations in the price of buying land have an effect on home prices. Furthermore, a significant portion of the building cost is the cost of the finished home. It is reasonable to suppose that housing costs influence home prices as well.
- The regional per capita GDP at the conclusion of the year, the population, and their disposable income are two examples of external indirect impacts. The absolute income level of the residents influences their home-buying behavior [7].
- In the home-buy function, the marginal purchasing power of housing decreases as consumer income increases, although overall data shows an increase in housing purchasing power [8].

### B. Challenges in Accurate Price Prediction

- A larger dataset can be considered with more features, like the swimming pool [8]. Parking space has a big impact on how much a property costs. Categorization of whether a property is a flat or a villa can provide different insights.
- The dataset used gets outdated with the passage of time due to government decisions, changes in locality, and constant updating is vital.
- It's found that images of house interiors have major impacts on pricing [9]. However, retrieving the interior design of the houses is not always possible.

## III. MACHINE LEARNING MODELS FOR HOUSING PRICE PREDICTION

The basic idea behind ML is to create algorithms that enable computers to learn [10]. The algorithm's input and intended result determine this. Certain ML methods will specify the methods that people can use to accomplish a job [11]. ML approaches and techniques have been developed by a number of mathematicians and programmers.

This section provides ML algorithms that are capable of analyzing the dataset and forecasting home values.

### A. Regression

The regression approach is used for two concepts. First, there are notable similarities between regression analysis and ML, which are commonly used for forecasting and prediction. Second, regression analysis may be used in some circumstances to determine the causal links between the independent and dependent variables [12]. Regressions alone,

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it should be noted, only display the relationships between a dependent variable and a dataset that has several components.

**Linear Regression**

The simplest ML technique, LR analysis, was used to test the calculating approach. Depending on the makeup of the independent variables, the MLR and PR methods were used [13][14]. Compared to other algorithms, LR performs similarly well, learns somewhat rapidly, and has a high explanatory power.

A sample regression procedure that simulates LR is the term for a linear relationship between one or more independent variables and a dependent variable [15]. The link between the independent and dependent variables is explained by the linear expression in Equation (1).

$$y = w_1 x_1 + b \qquad (1)$$

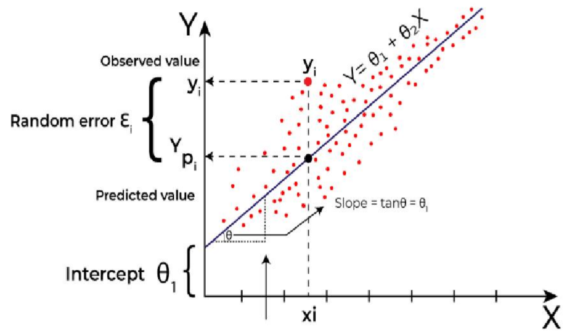


Figure 1: Linear Regression

**Decision Tree Regression Model**

In order to predict the value of the target variable, the DT algorithm-based choice tree regression model divides the input space into regions and fits a simple linear model to each one. The division is determined by a threshold of features to minimize the mean square error of the samples within each region [16]. DT regression models are capable of handling complicated data structures and non-linear correlations because they automatically manage feature interactions and non-linear relationships [17]. However, the DT approach is prone to overfitting issues and is extremely sensitive to noise and outliers.

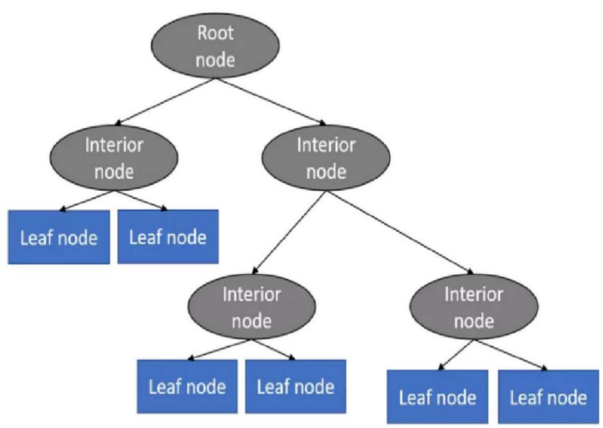


Figure 2: Decision Tree Regression Model

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**Random Forest Model**

A statistical technique called bagging is used to conduct regression and classification tasks concurrently. The RF method is an ensemble ML technique that uses a lot of DL to do both goals [18][19]. Instead of concentrating on a single DL, the RF model builds many DT with the data as the emphasis and combines their predictions to provide a more accurate and trustworthy forecast [20].

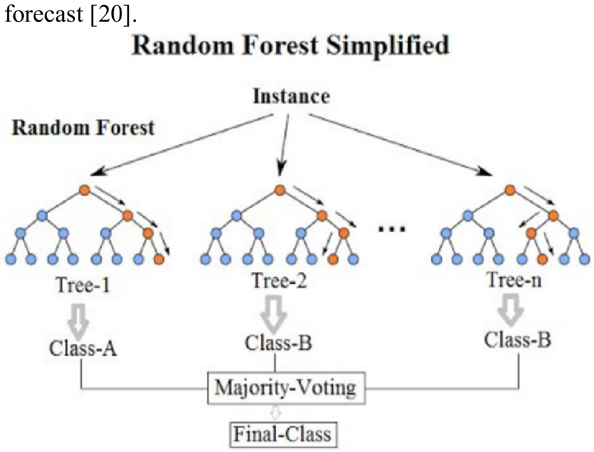


Figure 3: Random Forest Model

**Support Vector Machine Model**

The first step's detected SVM is then used as classifiers to predict future market moves. SVM can transform linear or non-linear input attribute spaces into high-dimensional feature spaces, which makes it helpful for modeling housing prices [21] and it is independent of the probability distribution assumption in Equation (2).

$$w^T x + b = 0 \qquad (2)$$

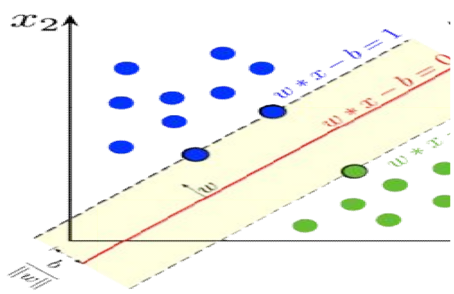

Figure 4: Support Vector Machine Model

## IV. DEEP LEARNING MODELS FOR HOUSING PRICE PREDICTION

One subfield of ML is DL. It is a method that uses numerous processing layers with complicated structures or multiple nonlinear transformations in an attempt to leverage the high-level abstraction of data [22]. DL is an algorithm used in ML that is based on characterizing learning data. DL and shallow learning are related concepts.

### A. LSTM (Long Short-Term Memory)

In this work, the TensorFlow and Keras libraries were used to build an LSTM prediction model. LSTM was created especially to manage sequential data's long-term dependencies [23]. The model may regulate the information flow and decide whether to accept or reject data according to its applicability to the current job by utilizing gate mechanisms [24]. This leads to an improved ability to manage long data sequences.


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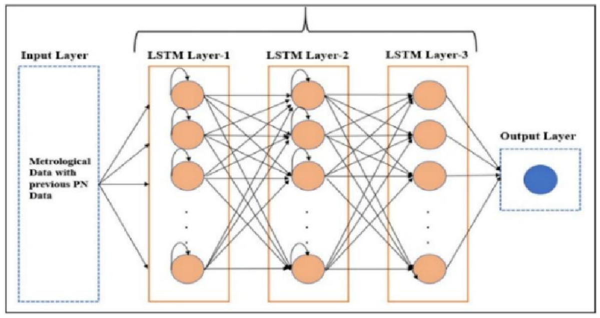


Figure 5: LSTM (Long Short-Term Memory)

**Application of LSTM (Long Short-Term Memory)**

- In a variety of problem areas, the LSTM network is used both alone and in conjunction with other deep learning designs.
- Time series data is the first thing that springs to mind when discussing temporal sequences in data. However, this is a wide idea. The LSTM model has been used to forecast financial markets in the more concrete context of time series forecasts [25].
- In terms of language acquisition, both context-free and context-sensitive, LSTM is a formidable force. In order to complete useful tasks, natural language processing examines how computers can understand and adapt to natural language speech or writing.

**B. RNN (Recurrent Neural Network)**

One of the ANN models made to handle sequential data, including text, audio, and time series, is the RNN. In contrast to classic neural networks that analyze inputs in a single forward pass, Recurrent connections in RNNs enable them to remember information from previous inputs and utilize it to affect how current inputs are processed [26]. It is clear that interpreting the present input requires knowledge of the context of previous inputs. Furthermore, because of their current state, they are highly suitable for language processing tasks, including machine translation, speech recognition, and language modeling [27][28]. The fundamental building block of an RNN is a sequence of recurrent cells, each of which updates its internal state in response to a new input. The cell transmits its output to the subsequent cell in the sequence after receiving input and its prior internal state from each time step [29]. As a result, the network is allowed to "remember" past inputs and utilize this information to inform how future inputs are processed.

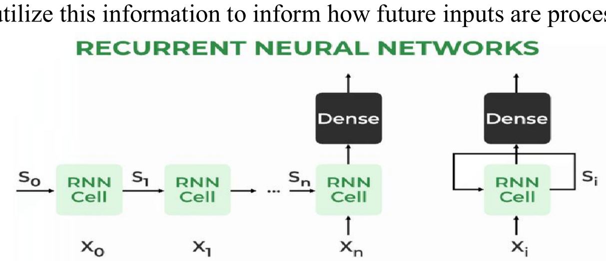


Figure 6: RNN (Recurrent Neural Network)

**Application of RNN (Recurrent Neural Network)**

- These have been RNNS that have revolutionized NLP by making such much more sophisticated, context-aware models possible. RNNs have been proven effective in several NLP tasks in several studies [30][31].
- Speech recognition has also benefited from significant contributions of RNNs [32], which have made it to more accurate and efficient system. This suggests that RNNs would be able to capture the temporal dependency in the speech signal and lead to A notational accuracy significantly higher than those using previous methods.

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- Anomaly detection in the security, industrial monitoring, and healthcare domains have all utilized RNNs [33]

## V. EVALUATION METRICS

The standardized assessment measures, including MSE, RMSE, and $R^2$, are used to thoroughly assess the models' performance.

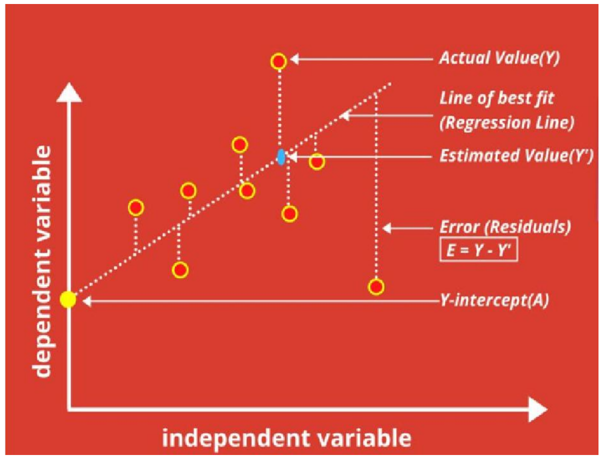


Figure 7: Regression Graph

Where,

- $p_i$ —predicted value
- $r_i$ —Actual Value
- $N$ — Total number of data points (samples)

**Mean Squared Error (MSE)**

MSEs are regression statistics that compute the average squared error between the predicted and actual values. It is supplied by and takes values that are either zero or positive Equation (3).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(p_i - r_i)^2 \quad (3)$$

**Root Mean Squared Error (RMSE)**

To quantify the discrepancies between the population or sample's actual values and those predicted by a model or estimate, another often used metric is the RMSE. The square root of MSE is this [34]. As an alternative, MSE and RMSE offer an error measure in the same unit as the target variable. It accepts values between [0, +∞) and is provided by Equation (4, 5):

$$RMSE = \sqrt{MSE} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - r_i)^2} \quad (5)$$

**R-Squared ($R^2$) Score**

To determine whether the given attributes have a negative, positive, or zero correlation with the house price, the Pearson Coefficient Correlation will be used. Additionally [35], for performance evaluation, the time required to train the model will be measured to demonstrate how the method varies over time in Equation (6- 9).

$$R^2 = 1 - \frac{SS_{Regression}}{SS_{Total}} \quad (6)$$

$$SS_{Regression} = \sum_{i=1}^{N}(p_i - r_i)^2 \quad (7)$$

$$SS_{Total} = \sum_{i=1}^{N}(r_i - p_i)^2 \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(p_i - r_i)^2}{\sum_{i=1}^{N}(r_i - p_i)^2} \qquad (9)$$

Where,

$SS_{Regression}$ – Sum Squared Regression Error

$SS_{Total}$ – Sum Squared Total Error

## VI. LITERATURE OF REVIEW

This literature review section reviews various ML and DL approaches for housing price prediction, emphasizing key methodologies, challenges, and contributions while highlighting the importance of macroeconomic indicators, preprocessing, and optimization techniques.

Kiran et al. (2023) describes their ML-based house price model and its dataset. Real estate data mining is frequent. Data mining can anticipate house values, essential property features, and more by extracting meaningful information from raw data. Research shows that property price variations worry homeowners and the real estate market. This paper discusses using Python modules to estimate housing prices using regression approaches. The proposed method utilized more precise house price calculations and provided more accurate predictions. It also discusses graphical and numerical methods for housing price prediction [36].

Nunna et al. (2023) In order to anticipate the HPI utilizing macroeconomic characteristics, they used a variety of time series, ML, and DL models in this work. Their objective is to obtain precise forecasts and connections that have a direct bearing on the real estate market. Numerous methods were used to anticipate HPI based on microeconomic characteristics, with minimal focus on macroeconomic characteristics such as national economic data. Accurately predicting housing price indices will be tremendously helpful to homeowners, banks, investors, and policymakers [37].

Sankar et al. (2024) present an investigation of landlord land price forecasting using ML techniques. The goal is to create a prediction algorithm that can precisely estimate land values so that landlords may make well-informed choices about their real estate investments. The research employs various ML algorithms, including but not limited to regression and ensemble methods, to analyze a dataset comprising relevant features, including demographics, economic factors, land size, and location. Through stringent testing and validation procedures, the prediction models' accuracy is assessed using performance measures such MAE, RMSE, and R2 [38].

Li and Li (2023) propose a blending model based on Python and its xgboost, DF21, and Geatpy packages to predict resale prices in Singapore. First, the high-cardinality categorical attributes are preprocessed by means of mean coding. Then, they propose a linear blending method that includes GA-HL-Xg-Boost, GA-RF, DRF, and lightGBM. To assess the significance of characteristics, use the Gini impurity. For both the government and individual investors, predicting the price of homes is crucial. The prediction system has high accuracy and flexibility and plays an important role in decision-making. However, previous studies have focused only on limited datasets, as well as non-time series or feature prediction [39].

Vijava et al. (2023) aim to give a summary of the most recent and widely used DL optimization methods that forecast more accurate and exact home values. This clever system takes on the responsibility of being essential to learning and optimization. However, because of their complexity, multidisciplinary nature, and dynamic nature, optimizing these systems is very challenging. One of the best tools for estimating regular fluctuations in property values is the HPI. The current house pricing data is processed using a variety of methods and considers a number of factors, such as layouts, design, climate control, etc [40].

Vaishnavi et al. (2024) illustrate the transformative impact of preprocessing on predictive models' reliability. Since it affects the decisions made by buyers, sellers, and investors, accurately estimating house prices is crucial in the real estate market. ML has emerged as a potent tool in this domain, leveraging historical sales data, property features, and economic indicators to forecast future prices. However, the quality of the data determines how well machine learning models work. Therefore, careful preprocessing procedures like feature engineering, normalization, and cleaning are required. Through techniques like data filtration and normalization, preprocessing refines data suitability for algorithms, enhancing predictive accuracy [41].

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Kaur et al. (2023) study article can assist in estimating a home's price, which benefits both buyers and sellers by enabling them to purchase a property at a fair price. The outcome demonstrated that machine learning methods in linear regression models are capable of making high-accuracy predictions about region pricing. Nevertheless, there are certain difficulties, such as the value of real estate according to its location, features, and amenities. In order to identify and fix the flaws, it stresses the use of ML algorithms for price prediction [42].

Table I highlights key research gaps in ML/DL-based housing price prediction, emphasizing data limitations, feature selection, optimization challenges, and forecasting improvements

Table 1: Comparative Analysis of Key Studies on Machine Learning and Deep Learning Models for Housing Price Prediction

| Reference | Focus Area | Key Findings | Challenges | Key Contribution |
|---|---|---|---|---|
| Kiran et al. (2023) | ML-based house price prediction | Regression models improve prediction accuracy | Limited dataset, lacks time series forecasting | Demonstrates the effectiveness of ML models for precise house price prediction |
| Nunna et al. (2023) | HPI forecasting with ML/DL | Macroeconomic factors significantly impact HPI | Less focus on microeconomic features | Highlights the importance of macroeconomic indicators in price forecasting |
| Sankar et al. (2024) | Land price prediction using ML | Regression and ensemble models yield high accuracy | Feature selection complexity, dataset limitations | Proposes predictive models for land price forecasting with rigorous evaluation |
| Li and Li (2023) | Blended ML models for resale price prediction | Linear blending models enhance prediction performance | Non-time-series-based approach limits adaptability | Introduces a blended approach combining multiple ML techniques for higher accuracy |
| Vijava et al. (2023) | DL optimization for precise price estimation | HPI provides key insights into housing trends | Complexity in optimizing dynamic systems | Explore deep learning techniques for improved price prediction accuracy |
| Vaishnavi et al. (2024) | Impact of data preprocessing on ML models | Preprocessing improves model reliability | Data quality issues affect prediction robustness | Emphasizes the role of data preprocessing in enhancing ML model performance |
| Kaur et al. (2023) | ML for estimating property prices | Linear regression achieves high accuracy | Area-based property valuation remains a challenge | Validates the efficiency of ML algorithms for property price estimation |

## VII. CONCLUSION AND FUTURE WORK

ML and DL models have emerged as effective tools for housing price prediction, offering accurate insights by analyzing complex datasets. LR, DT, RF and other, more advanced models like LSTM and RNN can also explain and ultimately show that they can extract linear and nonlinear relationships with the data. The results of these models are useful in helping more informed decision-making among homeowners, investors and urban planners. Nevertheless, the problems of data quality, feature selection and overfitting are issues that require continuous improvement with regard to model reliability and accuracy.

Future research is needed to combine various and real-time datasets (image and macroeconomic indicator) in order to increase the accurateness of prediction. Since an existing limitation of any single algorithm limits performance, hybrid models doing better than any individual algorithm may be explored. In addition, reinforcement learning and more sophisticated optimization techniques may be useful to model using when conditions change dynamically in the market. The other side of the coin is the need to consider the ethical aspects of automated systems, for instance, fairness and the


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possibility of bias of automated systems, for the sake of all stakeholders achieving fair outcomes. The usage of house price prediction models, which are now more reliable and useful, will be improved by these developments.

## REFERENCES

[1] R. Annamoradnejad and I. Annamoradnejad, "Machine Learning for Housing Price Prediction," 2022, pp. 2728–2739. doi: 10.4018/978-1-7998-9220-5.ch163.
[2] P. Chatterjee, "Smart Contracts and Machine Learning: Exploring Blockchain and AI in Fintech," Indian J. Sci. Technol., vol. 18, no. 2, pp. 113–124, Jan. 2025, doi: 10.17485/IJST/v18i2.3838.
[3] Q. Truong, M. Nguyen, H. Dang, and B. Mei, "Housing Price Prediction via Improved Machine Learning Techniques," Procedia Comput. Sci., vol. 174, pp. 433–442, 2020, doi: https://doi.org/10.1016/j.procs.2020.06.111.
[4] M. Jagan Chowhaan, D. Nitish, G. Akash, S. Nelli, and S. Shaik, "Machine Learning Approach for House Price Prediction," Asian J. Res. Comput. Sci., vol. 16, pp. 54–61, 2023, doi: 10.9734/ajrcos/2023/v16i2339.
[5] N. Panvelkar, P. Budkuley, C. Sawant, A. Mishra, A. Faldessai, and M. Dsouza, "Real Estate Price Prediction," Proc. - IEEE 2023 5th Int. Conf. Adv. Comput. Commun. Control Networking, ICAC3N 2023, vol. 10, no. 04, pp. 498–501, 2023, doi: 10.1109/ICAC3N60023.2023.10541544.
[6] S. Chatwani, M. Chotaliya, and V. Sawant, "House Price Prediction Review," Int. J. Comput. Appl., vol. 184, no. 7, pp. 35–39, 2022, doi: 10.5120/ijca2022922043.
[7] Y. Jiang and L. Qiu, "Empirical study on the influencing factors of housing price ——Based on cross-section data of 31 provinces and cities in China," Procedia Comput. Sci., vol. 199, pp. 1498–1504, 2022, doi: https://doi.org/10.1016/j.procs.2022.01.191.
[8] V. Pillai, "Anomaly Detection Device for Financial and Insurance Data," p. 2025, 2025.
[9] S. Suresh Yalgudkar and N. V. Dharwadkar, "A Literature Survey on Housing Price Prediction," J. Comput. Sci. Comput. Math., vol. 12, no. 3, pp. 41–45, 2022, doi: 10.20967/jcscm.2022.03.002.
[10] I. C. Udousoro, "Machine Learning: A Review," Semicond. Sci. Inf. Devices, vol. 2, no. 2, pp. 5–14, Nov. 2020, doi: 10.30564/ssid.v2i2.1931.
[11] S. R. Thota, S. Arora, and S. Gupta, "Hybrid Machine Learning Models for Predictive Maintenance in Cloud-Based Infrastructure for SaaS Applications," 2024, pp. 1–6. doi: 10.1109/ICDSNS62112.2024.10691295.
[12] D. Maulud and A. M. Abdulazeez, "A Review on Linear Regression Comprehensive in Machine Learning," J. Appl. Sci. Technol. Trends, vol. 1, no. 2, pp. 140–147, 2020, doi: 10.38094/jastt1457.
[13] S. Arora and S. R. Thota, "Using Artificial Intelligence with Big Data Analytics for Targeted Marketing Campaigns," no. June, 2024, doi: 10.48175/IJARSCT-18967.
[14] H. S. Chandu, "Efficient Machine Learning Approaches for Energy Optimization in Smart Grid Systems," IJSART, vol. 10, no. 9, pp. 67–75, 2024, [Online]. Available: https://ijsart.com/Content/PDFDocuments/IJSARTV10I999428.pdf
[15] S.-J. Kim, S.-J. Bae, and M.-W. Jang, "Linear Regression Machine Learning Algorithms for Estimating Reference Evapotranspiration Using Limited Climate Data," Sustainability, vol. 14, no. 18, 2022, doi: 10.3390/su141811674.
[16] V. P. Shashikant Tank Kumar Mahendrabhai Shukla, Nimeshkumar Patel, "AI Based Cyber Security Data Analytic Device," pp. 414425–001, 2024.
[17] Z. Li, "A Comparative Study of Regression Models for Housing Price Prediction," Trans. Comput. Sci. Intell. Syst. Res., vol. 5, pp. 810–816, 2024, doi: 10.62051/qjs7y352.
[18] A. Gogineni, "Advancing Kubernetes Network Stack for High-Performance AI/ML Workloads," Int. J. Sci. Technol., vol. 15, no. 4, 2024.
[19] M. I. Khan, A. Arif, and A. R. A. Khan, "The Most Recent Advances and Uses of AI in Cybersecurity," BULLET J. Multidisiplin Ilmu, vol. 3, no. 4, pp. 566–578, 2024.
[20] J. Jui, M. M. I. Molla, B. Bari, M. Rashid, and M. J. Hasan, "Flat Price Prediction Using Linear and Random Forest Regression Based on Machine Learning Techniques," 2020, pp. 205–217. doi: 10.1007/978-981-15-6025-5_19.

[21] Chen, J. H., C.-F. Ong, L. Zheng, and S.-C. Hsu, "Forecasting Spatial Dynamics of the Housing Market Using Support Vector Machine," Int. J. Strateg. Prop. Manag., vol. 21, pp. 273–283, 2017, doi: 10.3846/1648715X.2016.1259190.

[22] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," Neurocomputing, 2016, doi: 10.1016/j.neucom.2015.09.116.

[23] M. Shah and H. Sinha, "Automated Image Identification and Classification of Tiger Beetles Based on Deep Learning Model," in 2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, Jan. 2025, pp. 01125–01132. doi: 10.1109/CCWC62904.2025.10903740.

[24] S. Shi, "Comparison of Real Estate Price Prediction Based on LSTM and LGBM," Highlights Sci. Eng. Technol., vol. 49, pp. 294–301, 2023, doi: 10.54097/hset.v49i.8521.

[25] G. Van Houdt, C. Mosquera, and G. Nápoles, "A review on the long short-term memory model," Artif. Intell. Rev., 2020, doi: 10.1007/s10462-020-09838-1.

[26] A. K. Aftab Arif, Muhammad Ismaeel Khan, "An overview of cyber threats generated by AI," Int. J. Multidiscip. Sci. Arts, vol. 3, no. 4, pp. 67–76, 2024.

[27] A. Gogineni, "Chaos Engineering in the Cloud-Native Era: Evaluating Distributed AI Model Resilience on Kubernetes," J Artif Intell Mach Learn Data Sci 2024, vol. 3, no. 1, pp. 2182–2187, 2025.

[28] S. Chatterjee, "Integrating Identity and Access Management for Critical Infrastructure : Ensuring Compliance and Security in Utility Systems," vol. 8, no. 2, pp. 1–8, 2022.

[29] T. Tin, C. Wei, O. Min, B. Feng, and T. Xian, "Real estate price forecasting utilizing recurrent neural networks incorporating genetic algorithms," Int. J. Innov. Res. Sci. Stud., vol. 7, pp. 1216–1226, 2024, doi: 10.53894/ijirss.v7i3.3220.

[30] J. P. P. S. Nimeshkumar Patel Deval Parikh, Raghavendra Kamarthi Eranna, "Machine Learning Based Security Device For Cloud Computing," 418563–001, 2024

[31] A. R. A. Khan, M. I. Khan, and A. Arif, "Deep Learning in Cybersecurity in the Modern Era," JURIHUM J. Inov. dan Hum., vol. 2, no. 2, pp. 263–274, 2024.

[32] I. D. Mienye, T. G. Swart, and G. Obaido, "Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications," Information, vol. 15, no. 9, p. 517, 2024, doi: 10.3390/info15090517.

[33] V. N. W. Sunil Kumar, R Shantha Mary Joshitta, Deepak Dasaratha Rao, Syeda Masarath, "Storage Matched Systems for Single-Click Photo Recognition Using CNN," Int. Conf. Commun. Secur. Artif. Intell., 2023.

[34] V. Plevris, G. Solorzano, N. P. Bakas, and M. E. A. Ben Seghier, "Investigation of Performance Metrics in Regression Analysis and Machine Learning-Based Prediction Models," World Congr. Comput. Mech. ECCOMAS Congr., no. June, 2022, doi: 10.23967/eccomas.2022.155.

[35] I. C. Obagbuwa and S. Danster, "Housing Price Prediction Using Machine Learning Techniques," in 2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG), IEEE, Apr. 2024, pp. 1–12. doi: 10.1109/SEB4SDG60871.2024.10629723.

[36] A. Kiran, M. Khan, J. C. Babu, B. P. Santosh Kumar, and S. J. Ahmed, "Modeling House Price Prediction Model using XG Boost and Machine Learning Algorithms," in 2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), 2023, pp. 1–9. doi: 10.1109/ICCAMS60113.2023.10526190.

[37] K. C. Nunna, Z. Zhou, and S. R. Shakya, "Time Series Forecasting of U.S. Housing Price Index Using Machine and Deep Learning Techniques," in 2023 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 2023, pp. 1–6. doi: 10.1109/CSDE59766.2023.10487733.

[38] M. Sankar, R. Chithambaramani, P. Sivaprakash, V. Ithayan, R. M. Dilip Charaan, and D. Marichamy, "Analysis of Landlord's Land Price Prediction using Machine Learning," in 2024 5th International Conference on Smart Electronics and Communication (ICOSEC), 2024, pp. 1514–1518. doi: 10.1109/ICOSEC61587.2024.10722300.

[39] Z. Li and Z. Li, "Forecasting House Resale Prices using Ensemble learning," in 2023 2nd International Conference on Big Data, Information and Computer Network (BDICN), 2023, pp. 107–111. doi: 10.1109/BDICN58493.2023.00029.

[40] J. Vijava, P. S. Kumar, M. Sorgile, and M. S. V. Sv Vasanth, "Optimization Techniques for Deep Learning Based House Price Prediction," in Proceedings of the 2023 International Conference on Intelligent Systems for Communication, IoT and Security, ICISCoIS 2023, 2023. doi: 10.1109/ICISCoIS56541.2023.10100566.
[41] A. V. S. S. P. L. Vaishnavi, G. G. K. Raghavendra, M. Jilan, A. P. Chowdary, R. Singh, and K. C, "Exploring House Price Forecasting through Machine Learning and Data Preprocessing," in 2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN), 2024, pp. 304–310. doi: 10.1109/ICPCSN62568.2024.00055.
[42] H. Kaur et al., "Real Estate Forecasting System Using Machine Learning Algorithms," in 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), 2023, pp. 25–29. doi: 10.1109/IC3I59117.2023.10398134.