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Review Article

Machine Learning, Deep Learning, and Hybrid Approaches in Real Estate Price Prediction: A Comprehensive Systematic Literature Review

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Abstract: The real estate refers to an extensive field that deals with the purchase, selling, or management of properties, and it stands out as an influential industry in the economic development process, indicating that the precise determination of the price is one of the most effective tools for decision-making among different subjects of the market and authorities. Price prediction improves investment plans, risk management, fair price transactions, and provides key inputs to economic and urban planning. This systematic review categorizes the existing approaches into three groups: machine learning, deep learning, and hybrid models, based on the selected literature from a broad search of numerous databases and using rigorous criteria. The review indicates that the traditional and current machine learning models have relatively high levels of predictive accuracy for small datasets. However, deep learning techniques are preferable for handling large and complex data, while hybrid models have even more potential to increase prediction accuracy. The present study indicate that these sophisticated techniques can enhance and enrich price forecasting models, which can be insightful to various industrial decision-makers and informative for future research endeavours.

Keywords: Real Estate, Machine Learning, Deep Learning, Price Prediction, Hybrid Approach.

1. INTRODUCTION

In recent economic research and policy debates, considerable attention has been devoted to examining the impact of asset prices on macroeconomic policy. One such asset class that has played a significant role is real estate [1]. Real estate refers to land and all permanent structures or developments affixed to it whether natural or manmade. It encompasses houses, buildings, infrastructure, land and other precious resources like minerals, trees or water availability on the land. During the pandemic, the real estate market experienced significant shifts and continued expansion. The Real Estate Association estimates that in 2019 the GDP was boosted by the real estate sector by 7.62% [2]. The global economy is greatly impacted by the thriving real estate sector. The Asia-Pacific area had a 6% increase in transactions, while the European markets saw an 8% growth [3]. The entire spectrum of real estate investing and economic activity is included in the real estate market including transactions, investments, and ancillary services such as brokerage, appraisal, real estate consultancy, and management. It involves interactions among various stakeholders, such as real estate developers, sales representatives, prospective users, and intermediaries like brokers and appraisers. Real estate transactions are grounded in commodity and monetary relations, unfolding within specific temporal and spatial dimensions [4].

Real estate prices undergo analysis for rental assessments but their primary focus centers on property valuation often facilitated through automated valuation models. These statistically dependent automated valuation models provide current estimates of market values for particular properties based on real estate data including age, number of rooms, and comparable transactions in addition to pricing patterns. Valuations, a ubiquitous requirement, are frequently conducted by various market participants who work in real estate such

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as brokers, mortgage lenders, appraisers, investors, fund managers, market researchers, and analysts [5]. The real estate software market was anticipated to be valued at $9.73 billion in 2021 with an estimated growth rate of 9.7% from 2021 to 2028 [6].

The real estate market is important to the country's economy, as it plays a crucial role in many sectors lie urban planning, investment decision-making and formulating government policies. Thus, it is advantageous for investors, homeowners, government and regulatory bodies, and monetary authorities to keep an eye on market trends and make precise predictions on real estate prices. Moreover, the price prediction models help in risk evaluation, investment management, and preventing financial crises due to real estate market downturns. However, because there are so many direct and indirect variables that affect prediction accuracy [7]. The rising number of customer-reported post-purchase or post-rental regrets is causing industry anxiety. According to Trulia, 44% of real estate buyers regret their choices either purchases or rentals. This remorse is mostly attributable to a lack of knowledge about properties and the intricate nature of the acquisition procedure which leaves important information like fees hidden [8]. The current real estate management system cannot provide predictive insights into property prices for users.

Due to its multifaceted importance, many researchers have applied various techniques from traditional statistical models to advanced machine learning techniques. These traditional models include econometric models, and autoregressive integrated moving average models which have been used for real estate price prediction. However, recently machine learning techniques have radically changed the field, fostering the analysis of massive datasets and the recognition of complex patterns that traditional methods could not identify. Therefore, the use of machine learning to estimate real estate values is one of the most promising approaches [9]. This research aims to conduct a thorough examination of papers that are specifically focused on real estate price prediction. Our attention goes beyond the investigation of predictive algorithms to the technology that supports real estate price forecasting. Under close examination, we clarify the critical importance, diverse functions, and uses of high-tech methods—machine learning, deep learning, and hybrid approaches in real estate price prediction. An analysis of the previous studies reveals not only the complex workings of predictive models but also the revolutionary power and priceless insights provided by machine learning, deep learning, and hybrid approaches. This adds to the growing conversation about the nexus between technology and real estate. Furthermore, this study aims to reveal trends, difficulties, and possibilities within the existing literature that can serve as valuable information for further research and application of findings. By identifying the pros and cons of each strategy and showcasing how these technologies can be further employed strategically, we seek to enhance awareness of how these technologies can help address the emerging needs of the real estate industry.

Zulkifley *et al.* [10] examined machine learning algorithms for predicting home prices. Aspects classified as locational, structural, neighborhood, and economic factors were used in the investigations. XGBoost, multiple linear regression, artificial neural network, and support vector regression were utilized. Particularly, locational characteristics played a critical role in support vector regression, artificial neural network, and XGBoost's house value prediction. However, this study had limitations, such as a lack of a unified evaluation metric and a focus on specific attribute categories. Yalgudkar *et al*. [11] performed a survey on housing price prediction. This survey's strengths lie in the application of these diverse algorithms to predict housing prices, with notable mentions of accuracy improvements using random forest and gradient boosting. The survey provided insights into the challenges faced and suggests future research directions, accentuating the coupling effect of multiple regression models, exploring machine learning and deep learning methods, and finding efficient ways to apply complex models. Tekouabou *et al.* [12] explored machine learning applications in real estate prediction using SCOPUS-indexed papers from 2008 to 2022. With a peak in 2021, seventy-two articles were analyzed, revealing a preference for simple machine learning algorithms over deep learning. Dominant countries included China, the United States, and India. Common methods included decision trees, random forests, neural networks, boosting trees, support vector machine, and linear regression. Geerts *et al.* [13] analyzed 93 papers on residential property valuation, spanning from 1992 to 2021, categorizing them based on model and data novelty scores. The most widely utilized hedonic model types were structural equation modelling and multiple regression analysis. Utilizing random forest, gradient-boosted trees, neural networks, deep learning and other sophisticated machine learning techniques gained popularity. Conspicuously, the most recent papers (2020–2021) explored advanced machine learning and deep learning techniques with advanced spatial data, images, graphs, and text, indicating a shift toward more innovative approaches.

In Table 1, we present a summary comparing various surveys on price prediction in real estate, with an emphasis on the different machine learning and deep learning techniques used. Each reference is associated with its objective, the key models used in the study, and the limitations identified in the research. While existing studies have contributed valuable insights, there is a discernible gap in the comprehensive analysis of recent methodologies and their applicability to diverse real estate markets. Our goal is to synthesize findings from myriad sources, identify common trends, methodologies, algorithms, attributes, and features, address specific limitations in current approaches and highlight future development areas. By taking this approach, we hope to offer a more nuanced view of the current situation and offer fresh insights that will improve real estate price prediction models' precision and applicability.

The contribution of our paper is four folds given as follows:

- Based on comprehensive literature synthesis the existing approaches used for real estate price prediction are divided into three categories: machine learning, deep learning and hybrid model.
- This review provides a comprehensive analysis by integrating both qualitative and quantitative factors used to get more accurate real estate price prediction.
- In-depth analysis of algorithms and methodologies used in existing studies to highlight their strengths and address potential limitations.
- Providing valuable insights with practical implications for researchers, practitioners, and policymakers in real estate.

2. METHODOLOGY

This systematic literature review implements the preferred reporting items for systematic reviews and meta-analyses framework to assess the actual value of the real estate forecast, as shown in Figure 1. Systematic reviews and meta-analyses performed using the methodological approach of random search, selection, assessment, and result aggregation allowed the authors to maintain transparency, consistency, and repeatability at the screening stage of the review process. This explication of methodology covers the sequential phases of our data collating plan i.e. identification, filtering, inclusion screening, and eventually, inclusion, in full.

2.1. Identification

The first step includes a thorough survey of the relevant resources spanning a wide range of search tools in major academic databases. Google Scholar and Scopus were the two major databases

Table 1. Comparative Analysis.

Ref.	Objective	Key Models	Limitations
[10]	Evaluate house price prediction	MLR, SVR, ANN, XGBoost	Inconsistent RMSE reporting, limited focus on structural attributes.
[11]	Housing price prediction using ML/DL	MLR, Lasso, Ridge, SVM, RF, ANN, XG Boost	Need for larger datasets, consideration of additional features, and inclusion of global factors like inflation and GDP
[12]	Analyze ML in real estate prediction	DT, boosting trees, NN, RF, SVM, LR	Limited exploration of developing countries, bias towards structured data, and challenges in explainability.
[13]	Explore ML/DL trends in property valuation	MRA, SEM, RF, GBT, NN, DT, DL	Limited availability of large, high-quality datasets, challenges in handling diverse feature sets, potential gap between academia and industry practices

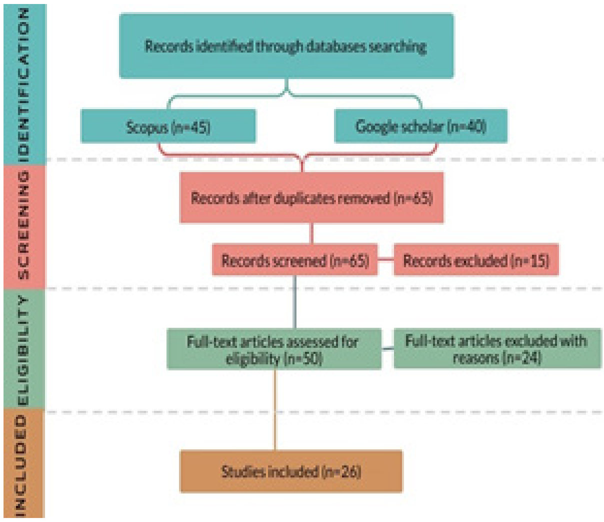

Fig. 1. PRISMA Framework.

that were used for the research investigation. In the interest of getting the most relevant papers out there on the prediction of real estate prices, a careful search strategy was designed. Searches with important words such as real estate, and price prediction, and their synonyms were used in the search engine. A total of 40 records were screened from Google Scholar and 45 records from Scopus were the initial search. These documents were then placed in the referencing software while maintaining the quality and gatekeeping role by eliminating duplicates. Table 2 outlines databases as well the search keywords that we have used in researching real estate price prediction. The data collection databases consist of Scopus and Google Scholar while the keywords are in real estate, price prediction, machine learning, and deep learning.

2.2. Screening

After removing duplicates, 65 unique records remained for further evaluation. During the screening phase, each record's title and abstract were studied to determine their relevance to our research question. Records that did not pertain to real estate price prediction were excluded at this stage. The screening process aimed to refine the list of potentially eligible studies.

2.3. Eligibility and Exclusion

Following the screening phase, the remaining 50 records were assessed for eligibility in more depth. We gathered full-text articles and carefully reviewed them to see if they satisfied the predetermined inclusion requirements. Criteria were set for the research including how good the work was, the possibility of the study to predict real estate prices and which method was used in the research. A total of 24 full-text publications were not included in the analyses because they were not qualified according to the rigidly set requirements. Thorough explanations were given for their exclusion and reasons for rejecting, which injected the decision-making process with transparency and fairness. Then, only twenty-six fulfilling articles that are resistant to the next phase are to be identified.

2.4. Inclusion

In the last step, we ended up with twenty-six studies which were based on certain specified parameters that we had predefined. The formation of our extensive research on real estate price projection partly depends on the studies we conducted. Therefore, the selected studies were incorporated into this systemic review based on the evidence of their methodology, the importance of their conclusions, and the strategies they used to address the main research issues.

3. FACTORS AFFECTING REAL ESTATE PRICE PREDICTION

It is typical to deal with qualitative or-quantitative features when discussing real estate and its attributes in an analysis of the real estate market. Qualitative characteristics are usually expressed orally. This provides information about the feature's status (such as its use as residential, recreational, agricultural, or industrial property) or allows for ranking variations (such as neighborhood characteristics, from most vulnerable to most compelling or from lowest to highest) [14]. The subjective preferences of

Table 2. Databases and Search Keywords.

No.	Databases	Keywords
1	Scopus	("real estate" AND "price prediction") OR ("real estate" AND "machine learning") OR ("real estate" AND "deep learning") OR ("real estate" AND "hybrid")
2	Google Scholar	("real estate" AND "price prediction") OR ("real estate" AND "machine learning") OR ("real estate" AND "deep learning") OR ("real estate" AND "hybrid") OR "land price"

decision-makers regarding viewpoints, architectural styles, and living situations are included in these qualitative components. However, a lack of accurate measurements can occasionally affect the qualitative results for these factors. Conversely, real estate characteristics, business cycles, and macroeconomic factors can all be considered quantitative factors. Metrics such as industrial production, gross domestic product, share indexes, unemployment rates, and a nation's current account are examples of macroeconomic factors. Past selling prices, land acreage, building years, floor area, surface area, number of stories, and building conditions are all considered real estate features [6]. Figure 2 shows a summary of the attributes involved in real estate price prediction.

3.1. Quantitative Attributes

Quantitative attributes in real estate provide measurable, numeric insights for objective analysis. Macroeconomic indicators like unemployment rates, share indexes, current accounts, industrial production, and gross domestic product offer a broad economic context. Attributes like past sales prices, land area, construction year, floor space, surface area, number of floors, and building conditions that accompany the characteristics of the property in question may form property-specific quantitative attributes. This criterion lets the stakeholders acquire analytical algorithms and data on the way to make sound decisions and conduct a full assessment of the economic viability and investment avenues.

Fig. 2. Attributes involved in the real estate.

3.2. Qualitative Attributes

The qualitative factors that are inseparable from real estate include subjective and non-numeric elements which give beauty to a property. The use of the property, either for housing, recreation, farming or industry, determines its respective role. Classification of a neighborhood as unfavorable, average, or favorable is according to certain features. Cultural peculiarities in architecture appear in the form of view preferences, building types, and the living environment. Although these subjective aspects are not measured with exactness, these qualitative factors have a considerable impact on the perceived desirability adding to a broad comprehension of a property's market value. A comprehensive analysis of the real estate property typically involves qualitative and quantitative parameters which is important for a better understanding.

4. TECHNIQUES USED FOR REAL ESTATE PRICE PREDICTION

This section scrutinizes methodologies outlined in the targeted scholarly articles, classifying them into three distinct categories: machine learning, deep learning, and hybrid-based techniques. This part of the discussion deals with the main ideas of each academic paper which is in the main target. Figure 3 provides an extensive examination of machine learning, deep learning, and hybrid approaches used in the selected studies. This visual aid provides a synopsis of the many methodologies employed in the research, exhibiting the range of models and techniques employed for different purposes, including real estate analysis and price forecast. This figure contributes to a comprehensive knowledge of the approaches used in the area by offering a consolidated perspective of the methodological landscape utilized in the analyzed publications.

4.1. Machine Learning

Artificial intelligence's machine learning discipline enables computers to learn from large, complex datasets without the need for explicit programming [15]. Through the application of mathematical and statistical tools, machine learning endows

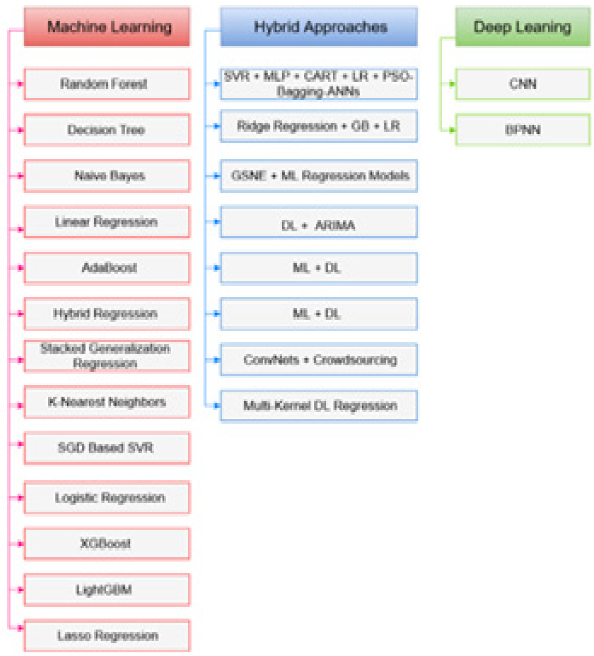

Fig. 3. All the methodologies mentioned in targeted studies.

machines with the ability to autonomously execute intellectual tasks that were traditionally the domain of human beings [16]. Essentially focused on deriving models from data, machine learning, often employed for prediction purposes, is intrinsically linked with the notion of uncertainty [17]. Since the 1990s, academic research has investigated machine learning use in predicting residential prices. Machine learning-based models are a good option for stakeholders looking to forecast home prices because of their effectiveness in solving problems that are beyond the scope of human capacity.

The capability of machine learning techniques to find functional connections in historical records has been demonstrated by the widespread use of these algorithms to anticipate real estate values in recent years [18]. Within machine learning, there are three categories:

- Supervised Learning: It uses example input-output pairs to build a function that draws inputs to outputs based on labelled training records. This method uses tagged samples to infer the intended function based on a predefined set of objectives [19].
- Unsupervised Learning: By evaluating unlabeled datasets without the need for human interaction, it highlights a data-driven approach [19].
- Semi-supervised Learning: It is a hybrid technique that may be used for both labelled and unlabeled data. It blends aspects of supervised and unsupervised approaches. Semi-supervised learning, which falls in between "without supervision" and "with supervision," is especially useful in real-world situations when there is a dearth of labelled data and a surplus of unlabeled data. Predictions produced with a semi-supervised learning model should ideally perform better than those made with only tagged input [19].

Gampala *et al.* [20] used a methodology that utilized supervised learning algorithms within the domain of machine learning. The researchers used a variety of techniques, including random forest classification [21], decision trees [22], naive bayes [23], and linear regression [24]. The researchers concluded that linear regression proved to be the most effective in predicting house values based on the provided dataset.

Tchuente *et al.* [25] used machine learning algorithms, covering neural networks (MLP), random forest, adaboost [26], gradient boosting [27], and KNN [28]. For neural networks, specific hyperparameters include variations in network architecture, activation functions, learning rates, and optimizers. The best-performing ensemble learning techniques - random forest, AdaBoost, and gradient boosting are emphasized. The researchers highlighted the crucial role of geographic coordinates, introduced through geocoding, in enhancing the predictive accuracy of these models.

Uzut *et al.* [29] discussed data mining methods and focused on three primary methodologies: linear regression, random forest, and gradient boosting. 414 real estate properties are included in the dataset, which was gained from the University of California, Irvine. The outcomes of their research divulged that the gradient-boosting algorithm attains the highest accuracy.

Al Kurdi *et al.* [30] used many classification methods for modelling [31] and forecasting resale home values, including decision tree, random forest, AdaBoost, naïve bayes, and logistic regression. Decision tree C5.0 showed remarkable accuracy, a TNR over 92%, and a TPR above 92% when the study evaluated the performance of many algorithms.

Three machine learning techniques were applied by Ho *et al.* [32]: SGD-based SVR [33], random forest, and gradient boosting. The researchers compared these algorithms to estimate housing prices, emphasizing their accuracy and prediction capabilities. While support vector machine was highlighted for its computational efficiency, random forest and gradient boosting demonstrated superior predictive accuracy with lower errors. The study concluded that machine learning, specifically random forest and gradient boosting, holds promise for accurate property price predictions.

To assess the prices of real estate transactions in Taichung, Taiwan, Pai *et al.* [34] employed BPNN [35], CART [36], GRNN [37], and LSSVR [38] to gather, purify, and restructure real estate attribute data. Genetic algorithms [39] were utilized for model parameter optimization, and a 5-fold cross-validation assessed model robustness. As a consequence, three machine learning models provided extremely accurate predictions, while one performed well. The LSSVR model standed out as the most accurate, surpassing previous studies in MAPE measurements.

Truong *et al.* [40] focused on random forest, XGBoost, and lightGBM for housing price prediction. The researchers introduced hybrid regression and stacked generalization regression [41]. Data analysis highlighted location, age, and various features' impact on prices. The evaluation measure was RMSLE. Random forest exhibited low overfitting, while hybrid regression outperformed the training set. Stacked generalization regression exceled in generalization on the test set. Further research was suggested on factors influencing tree-based model performance and combining machine learning, deep learning methods.

Dalal *et al.* [42] discussed the application of support vector regression for predicting real estate prices in China. It reviewed various studies on real estate market determinants. support vector regression was contrasted with BPNN. The results of the investigations revealed that the SVR model outperformed the BPNN model in terms of MAE, MAPE, and RMSE.

Sanjar *et al.* [43] investigated real estate price variation in Taipei, Taiwan, focusing on the Cathay House Price Index and Sinyi Home Price Index. BPFNN and RBFNN were applied with 11 macroeconomic parameters as input for predicting price variations. The study compared the prediction performance using MAE and RMSE. For the Cathay index, RBFNN outperformed BPFNN, achieving lower MAE and RMSE compared to BPFNN. Conversely, for the Sinyi index, BPFNN exhibited better performance with lower MAE and RMSE compared to RBFNN.

Ziweritin *et al.* [44] discussed three main methodologies: linear regression using square feet as a feature, multivariate regression models using multiple features, and polynomial regression with features raised to different powers. The study evaluated the performance using RMS value. Among the models, the multivariate regression model with features of square feet, bedrooms, and bathrooms harvested the best result.

Haque *et al.* [45] used various regression techniques, comprising multiple linear regression, ridge regression, lasso regression, elastic net regression, adaptive regression, and gradient boosting regression, focusing on Vijayawada, A.P. datasets. It compared algorithms based on scores, MSE, and RMSE. Gradient boosting regression achieved the highest accuracy.

Lee *et al.* [46] investigated the use of machine learning, particularly linear regression, support vector regression, k-nearest neighbors, and random forest, in real estate price prediction. With the lowest prediction error of 0.3713 among all techniques, linear regression produced the best outcomes.

Adetunji *et al.* [47] utilized random forest. The authors used the UCI Machine Learning repository Boston housing dataset with 506 entries and 14 features. This study used MAE, R^2, and RMSE to weigh the model's enactment. The consequences indicated that the random forest predicted house prices with an acceptable difference of ±5 compared to actual values.

Li *et al.* [48] involved the use of the LightGBM framework. The study compared different approaches, including neural networks, and concluded that the LightGBM model, augmented with logarithmic transformation, geo data, and apartment brand information, produced the best MAPE results.

Matey *et al.* [49] used linear regression, lasso regression, and decision tree. Among these, linear regression attained the preeminent result by an accuracy of 83.54%. This study focused on data collection from various sources such as Kaggle, Magicbricks, 99acres, and government websites.

Rizun *et al.* [50] explored various methodologies including hybrid models, fuzzy logic, artificial neural networks, k-nearest neighbors, and machine learning techniques such as decision tree, random forest, naive bayes, logistic regression, and AdaBoost. Among these methods, the paper identified the decision tree using C5.0 and AdaBoost as particularly effective for the dataset, with the decision tree concentrating on rule generation and providing the best accuracy results accuracy, TNR, and TPR, all above 92%.

4.2. Deep Learning

Over the past few decades, advances in sophisticated learning algorithms and efficient pre-processing techniques have led to considerable advancement in machine learning. The evolution of ANNs into increasingly intricate structures, which gave rise to what is now known as deep learning, has been a noteworthy milestone in this trajectory [51]. Deep learning, a specific category within machine learning, comprises multiple layers of ANNs, offering a high-level abstraction for data modelling [52]. In several domains, including natural language processing, gaming, and image processing, it has demonstrated the ability to provide superior prediction outcomes [53]. Deep learning is the most well-liked and generally acknowledged use of artificial intelligence. Well-known tech companies like Google, Microsoft, Facebook, and Amazon have made substantial financial commitments to the study and development of this technology. As of 2016, Google alone claimed to have contributed to over 1,000 deep-learning projects. Currently, a variety of activities require these systems, such as text translation, speech recognition, photo tagging, finding new exoplanets, playing strategic games, evaluating fMRI data, and enabling autonomous driving of automobiles [54].

Zhan *et al.* [55] used backpropagation neural network and convolutional neural network [56] using dataset that included macroeconomic factors and home features from Taiwanese real estate transactions between January 2013 and December 2018. The study contrasted two scenarios: one that incorporated macroeconomic data into its prediction, and the other that solely used home qualities. PCA and normalization were used in the data preprocessing to improve model performance. The assessment measures consisted of r-square, adjusted r-square, MAE, MAPE, RMSLE, and RMSE. With an emphasis on a 5-month historical data span, the results showed that convolutional neural network performed better than backpropagation neural network in predicting house values.

Xu *et al.* [57] anticipated housing prices using deep learning techniques, including convolutional neural network. This study's convolutional neural network model had two convolutional layers, a modified loss function for continuous value regression, and a dropout structure to prevent overfitting. The kind of home, the building area, the location, and macroeconomic variables, for example, GDP, property asset, and consumption level are among the features that have been chosen for prediction. The convolutional neural network model's efficacy was validated by the experimental results, which showed a mean square error of 0.01057 and an accuracy of 98.68%.

4.3. Hybrid Approach

Nouriani *et al.* [58] adopted a hybrid approach, combining deep learning and time series forecasting methods for predicting house prices. The researchers initially employed a deep learning model to predict individual house prices. The model in use consisted of four hidden layers, one output layer with projected house values, and one input layer with property features. The deep learning model was trained by forward and backpropagation with an Adam optimizer. This study forecasted the trajectory of property prices using the prevalent time series projecting method. This model accounted for the temporal aspects of fluctuations in housing values. Due to the researchers' emphasis on the intricate nature of the interaction between influencing elements and housing prices, a dual technique for an all-encompassing prediction approach was adopted.

Chou *et al.* [59] anticipated housing prices using a hybrid strategy that incorporated aspects of ensemble and optimization techniques. The researchers employed machine learning techniques such as support vector regression, multilayer perception (ANNs), CART, and linear regression as baseline models. Furthermore, it improved prediction performance by employing ensemble techniques, particularly bagging ANNs. A hybrid model known as PSO-Bagging-ANNs combined the use of particle swarm optimization (PSO) for ANN parameter optimization with bagging for aggregation.

Kabir *et al.* [60] used a hybrid approach combining feature engineering and multiple regression algorithms. The methodology involved creative feature engineering, including transformations, category changes, and the introduction of new variables. The study utilized ridge and lasso regressions, along with gradient boosting, as the main regression algorithms. The feature selection was performed using lasso, and a hybrid regression model was proposed, combining lasso and gradient boosting with different weightings. The results indicated that this hybrid method outperformed individual regression algorithms.

Das *et al.* [61] used a hybrid approach, combining machine learning techniques with a specialized embedding model called geospatial network embedding (GSNE). In the hybrid method, the GSNE model which was intended to gather and incorporate neighborhood information based on housing's proximity to different points of interest (POIs) such as areas, schools, and train stations was used in concurrence with machine learning regression models.

Wang *et al.* [62] utilized disparate data from real estate transactions, public facilities, and satellite maps. Based on the input characteristics, the research did a comprehensive preprocessing and separated the data into 13 attribute groups. When metrics for assessment like MAPE were used to compare the numerous machine learning, deep learning models, XGBoost performed better than its machine learning counterparts, and deep learning models that integrated data from public facilities and satellite maps performed better than their machine learning counterparts. Attention mechanisms, particularly the joint self-attention model, were introduced and proven to enhance model flexibility and accuracy. The Joint Self-Attention model performed the best. Krishnasamy *et al.* [63] used a hybrid approach for live guideline value (GV) prediction in land pricing across Chennai's metropolitan area. The methodology involved utilitarian association rule mining, utilizing 30 customer land-buying pattern attributes obtained through questionnaires. Spatial parameters were measured using GIS, and models like ANN [64] and associative multilayer perceptron [65] were proposed for GV prediction. Potrawa *et al*. [66] explored automated real estate valuation, accentuating visual impact on house market values. It introduced a framework combining ConvNets and crowdsourcing for luxury-level estimation using Zillow data. The proposed method surpassed Zillow's estimates, achieving a 5.8% median error rate compared to Zestimate's 7.9% which showcased the effectiveness of incorporating visual features in real estate valuation.Yousif *et al.* [67] examined many studies that used different approaches, including regression models, hybrid models, and machine learning models, to forecast home prices. They suggested creating a brand-new benchmark dataset called REPD-3000, which included textual and visual data for 3000 dwellings. With the lowest MAE values of 14.38 and 16.60 for REPD-2000 and REPD-3000, respectively, their suggested multi-kernel deep learning regression model beated alternative techniques, such as a multi-kernel SVR.

Table 3 presents a representation of machine learning, deep learning, and hybrid approaches, showcasing different algorithms, metrics and their corresponding accuracies.

5. ANALYTICAL DISCUSSION

Real estate price prediction is a challenging task that needs analysis of various qualitative and quantitative factors. Initially, we have selected 193 attributes but after thorough study, several qualities were unnecessary and hence removed. The remaining 141 attributes were then methodically classified into two categories: qualitative (37) and quantitative attributes (104). By leveraging this mix of attributes, a rich picture of the real estate environment for the sake of understanding key variables that influence property dynamics is provided. Therefore, these attributes compound the focus and are good for anyone interested in understanding how various inputs drive the real estate dynamics.

Table 3. Summary of Machine Learning, Deep Learning, and Hybrid Approaches Analysis: Algorithms, Metrics, and Accuracy.

Ref.	ML Algorithms	Metrics									Accuracy
		Qualitative						Quantitative			
		Macro-economic					Others	PP	N	SP	
		UR	SI	CA	IP	GDP					
[20]	RF, DT, NB, LR	✓	✓	✓	✓						-
[25]	MLP, RF, AdaBoost, GB, KNN						✓				-
[29]	LR, RF, GB										LR: 63-68%, RF: 74-78%, GB: 77-78%
[30]	DT, RF, AdaBoost, NB, Logistic Regres-sion						✓				Logistic Regression: 81.5%, DT: 92%, RF: 86.5%, NB: 88%, AdaBoost: 96%
[32]	SGD based SVR, RF, GB										SVM: 82.7%, RF: 90.3%, GB: 89.4% (base model); 90.4% (after hyperpara-meter tuning)
[34]	BPNN, CART, GRNN, LSSVR						✓	✓			LSSVR: MAPE - 0.228%, NMAE - 8.11 x 10^(-4)
[40]	RF, XGBoost, light-GBM, HR, SGR										RMSE - 7671, MRE - 0.22
[42]	SVR, BPNN										SVR (MAE: 1.363, MAPE: 0.01, RMSE: 1.893) BPNN (MAE: 1.788, MAPE: 0.017, RMSE: 2.481)
[43]	BPFNN, RBFNN					✓					-
[44]	LR, MVR, PR										-
[45]	MLR, RR, LR, ER, AR, GBR								✓		MLR (MSE: 391875744, RMSE: 197958) RR (MSE: 391740496, RMSE: 197924) LR (MSE: 391875537, RMSE: 197958) ER (MSE: 489642930, RMSE: 221278) AR (MSE: 32161481079, RMSE: 179336) GBR (MSE: 12037006088, RMSE: 109713).
[46]	LR, SVR, KNN, RF Regression										-
[47]	RF										-
[48]	LightGBM						✓				MAPE values: NN - 10.832%, LightGBM - 9.603%, LightGBM + log - 8.598%, LightGBM + log + Geo Data - 8.412%, LightGBM + log + Geo Data + Brand - 8.349%.
[49]	LR, Lasso Regression, DT						✓				Linear Regression (83.54%), Lasso Regression (82.92%), DT(77.88%)

[50]	DT, AdaBoost					-
[55]	BPNN, CNN	✓				-
[57]	CNN					GM: ~90%, XGBoost: ~96.5%, CNN: ~98.68%
[58]	DL (Forward and Backpropagation with Adam optimizer)				✓	-
[59]	SVR, MLP, CART, Linear Regression + PSO-Bagging-ANNs (Particle Swarm Optimization + Bagging)		✓		✓	-
[60]	Ridge Regression, Lasso Regression, GB (Hybrid Regression)				✓	-
[61]	GSNE + ML Regression Models		✓	✓		-
[62]	ML + DL (XGBoost, Joint Self-Attention Model)					-
[63]	ML + DL (ANN, Associative MLP)		✓			-
[66]	ConvNets + Crowdsourcing		✓			-
[67]	Multi-Kernel DL Regression		✓			-

Figure 4 illustrates the allocation of research papers across various categories, highlighting the predominance of studies in machine learning, deep learning, and combinations of both methodologies. Among the examined studies, the greatest emphasis is on machine learning (61.5%), trailed by hybrid methodologies (30.8%), with a lesser portion devoted to deep learning (7.7%). The distinct colors in the chart emphasize each category and provide a clear and concise overview of the research distribution in the specified domains. Given the widespread adoption of machine learning in the majority of the targeted research papers, a more in-depth examination of the distribution of machine learning categories was conducted. Figure 5 provides a visual breakdown, showcasing the prevalence of specific machine learning categories. Among the various machine learning categories explored, regression emerges as the most prominent, representing 30.8% of the total distribution and is followed by classification and data mining, each constituting 15.4%. Other categories include supervised learning, gradient boosting, and various machine learning approaches. This visually appealing representation aids in understanding the distribution and emphasis of machine learning methodologies in the examined studies.

Table 4 combines and extends the insights gained from Figure 6, illustrating the percentage distribution of methodologies used in predictive modelling across various research papers. The methodologies, namely machine learning, deep learning, and hybrid approaches are presented alongside their respective percentages of representation in the papers. According to analysis machine learning is recognized for its versatility in diverse applications and well-established algorithms, albeit with potential challenges in handling complex patterns and unstructured data. Deep learning is highlighted for its excellence in managing complex data relationships and effectiveness in image and speech recognition. However, it demands substantial computational resources. The hybrid strategy increases predicted accuracy by conjoining the benefits of deep learning and machine learning. Nevertheless, this approach introduces increased complexity in model design and potential challenges in integration. Together, these findings offer a comprehensive understanding

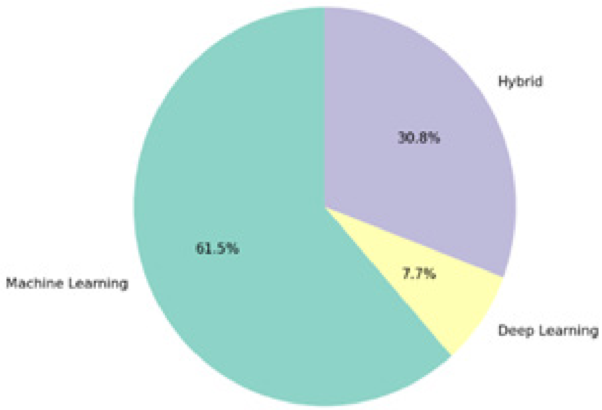

Fig. 4. Distribution of papers by methodology.

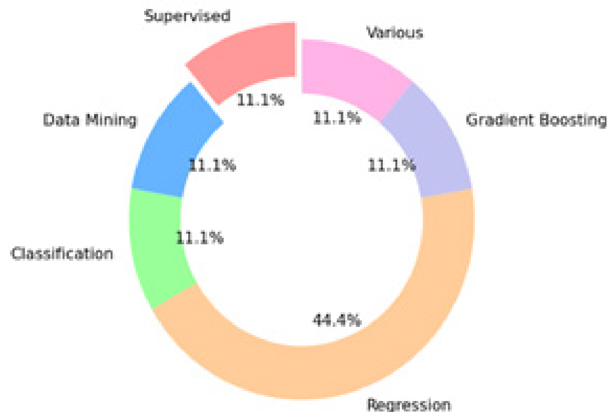

Fig. 5. Distribution of machine learning categories.

of the methods that are frequently employed in real estate predictive modelling, along with the benefits and drawbacks of each.

Figure 6 illustrates the distribution of various machine learning algorithms across the targeted studies. The data reveals a diverse machine learning techniques employed. Linear regression and decision trees stand out as the most frequently utilized algorithms, each appearing in 6 studies. Random forest, AdaBoost, and gradient boosting also demonstrate notable usage with counts of 6, 3, and 4, respectively. This visualization provides insights into the popularity of machine learning algorithms, helping in understanding the methodological preferences within the examined research studies. The color-coded bars enhance the visual appeal, making it easier to discern the distribution and relative prevalence of each algorithm. Figure 7 illustrates the distribution of the number of variables reported across the studies reviewed in this paper. The x-axis represents the number of variables used in each study, while the y-axis lists the corresponding references. For example, reference [67] utilized 15 variables, [63] used 8 variables, [62] utilized 13 variables, and [61] used 43 variables. Some references, such as [20, 45, 49, 50, and 66] are marked as “unknown”, indicating that the number of variables was not explicitly mentioned in these studies. This distribution highlights the inconsistency in the number of variables considered across the targeted research studies.

6. CONCLUSIONS

In summary, this review represents the applications of machine learning, deep learning, and hybrid models making substantial advancements with enhanced accuracy and deeper insights for real estate price prediction. The comprehensive literature review categorized existing approaches into three primary categories: machine learning, deep learning and hybrid approaches. Machine

Table 4. Methodologies in real estate predictive modelling.

Tec.	Papers %age	Merits	Demerits
ML	61.5%	• Versatility in diverse applications • Well-established algorithms and models	• May struggle with complex patterns • Limited in handling unstructured data
DL	7.7%	• Excellent for complex data relationships • Effective in image and speech recognition	• Requires substantial computational resources
Hybrid Approach	30.8%	• Combines the strengths of ML and DL • Improved predictive accuracy	• Increased complexity in model design • Potential challenges in integration

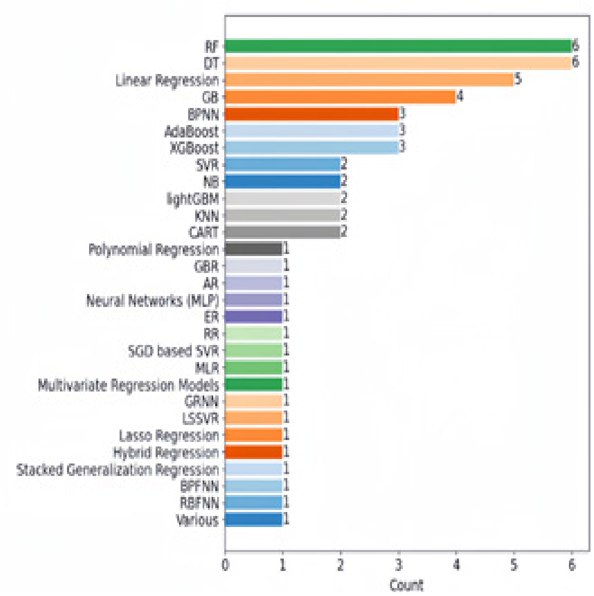

Fig. 6. Distribution of ML algorithms.

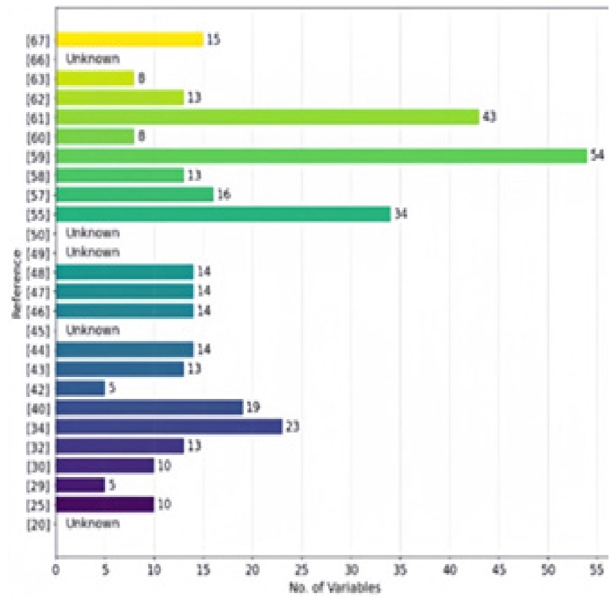

Fig. 7. Distribution of number of variables.

learning is used in 61.5% studies due to its flexibility and well-established methodologies, but it has difficulties in recognizing diverse patterns and working with unstructured information. Deep learning is applied in 7.7% studies, highlighting its potential of managing complex data relations, but has heavy computational penalties. As highlighted in one-third of the studies, hybrid solutions were used as being highly effective since they integrated both ML and DL to improve the prediction capability. According to the findings of this review, machine learning is the most prevalent technique in real estate price prediction, although deep learning and hybrid techniques are gaining increasing attention. By comparing and contrasting these three approaches, this analysis provides insight into the strengths and limitations of each, which is beneficial for both researchers and practitioners. However, there were some research gaps and limitations noted in the current study. Specifically, there is challenge of computational resource requirements in deep learning and the increased demand for improving the data processing of unstructured data in the machine learning domain. Also, the number of studies concerning deep learning is also significantly smaller, which points to the fact that this field has been researched less despite the ability to use this approach for the real estate price prediction. The review suggests that future research should be directed at filling these gaps by identifying better performing algorithms, and examining the possibility and scope of using multiple forms of data, under different market conditions. In doing so, academicians, researchers and professionals in the real estate will be better placed in identifying patterns that will aid in obtainment of better accuracy in their valuation and prediction models.

7. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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