



Analyzing House Sales Prices by hyperparameters tuning Method Using Deep Learning (DL) Techniques

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Abstract

One of the familiar trends in this world is house price prediction whereas the researchers have performed their studies using Deep Learning (DL) techniques. The prediction model development in house price trends help the real estate agents or selling house owners for determining better decision making over predicting house price. The existing model in predicting house price is not provided with sufficient data which may affect the house prices that need to be considered for predicting the house prices accurately. However, the accurate house pricing prediction is essential to several bodies involved in the businesses of real estate are property owners, building contractors, real estate organization as well as banks and financial sectors. Hence, the end to end support is a significant factor to a model for prediction of house pricing. Thus, the paper focuses on hyperparameter tuning protocol which gets implemented in Convolution Neural Network (CNN) technique by optimizer sensitivity. The optimizer which involved in this model is based on Learning Rate (LR) adoption in which seven optimizers are selected and implement with house sales price dataset. The various outcomes from the optimizer with several epochs are analyzed that have capable of hyperparameter tunability on DL method of CNN model. The best optimizer provide less Error Rate (ERR) as well as high accuracy is evaluated have been considered as an improved CNN model for predicting the better house sales price. This proposed CNN model assist house buyer and also for house seller to predict the exact house sale price based on their requirements.

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Key Words: Deep Learning (DL), Convolution Neural Network (CNN), House Price Prediction, hyperparameter

DOI Number: 10.14704/nq.2022.20.8.NQ44159

NeuroQuantology 2022; 20(8):1452-1460

1. Introduction

As like other property market, housing market is also understandable that can be operated whether directly from an owner to buyer or services through real estate brokers. The attention of several individuals and organizations over this house market may presented with high opportunities of profit that can be accomplished through global housing demands. There are various factors like economy, politics and demography plays the major role in influencing these demands. Due to this reasoning, the housing market analysis has become challenging all over the world to data analyst as well as Machine Learning (ML) engineers. These kinds of challenges need to be addressed, various data type with large scientific fields range to accomplish

accurate results for stakeholders and customers [1, 2] are utilized. Based on the analysis of transaction records, buyers can recognize that received house price is fair or not as well as the seller can able to estimate the house price who can sell the house with particular road section. In the application of financial technology, prediction of house price is considered to be required with reasonable estimation system to mortgage estimation as well as house auctions.

The learning can be accomplish at several levels through DL in which inputs have been progressed as an initial level and get transformed in form of conceptual at the subsequent level until the process is turned in to precise form. Similarly, the learning can be obtained deeper.

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When compared to Hybrid Predicting Modelling (HPM), regression methods have obtain slight better results but the setting cost is expensive as well as highly complex. The Artificial Neural Network (ANN) based technique is considered as an alternate for traditional method in predicting house price method shown a beneficial outcome while implemented for estimating real estate business [3, 4]. The major advantage of choosing ANN is capable of identifying non-linear relationship among inputs and outputs which determines that ANN is appropriate to non-linear prediction of housing price prediction as well as evaluation [5]. CNN technique is the inspired form of ANN architecture whereas the performance gets minimized over object detection regions and issues of image classification. However, the CNN model availability is more suitable over image processing areas have increased to large extent that provide clarity in several concept and even provide solutions in various methods [6]. Hence, the CNN can accomplish essential benefits over areas of computer visions, speech recognitions, natural language processing, etc. This is a network structure with multiple trained layers that consists of various layers [7]. The build model by DL methods namely CNN and Recurrent Neural Network (RNN) whereas initially understand CNN are utilized primarily for identifying or recognizing the images that considered as computer vision. It assists to generate computers by understanding images and videos which is utilized to recognize optical character, smile detection, face detection, etc. Thus, the supervised DL method is CNN which perform big breakthrough over computer vision fields.

The selection of optimization algorithm from DL experts has determines the speed of training and overall model predictive performance. At present, there is no idioms with sufficient explanation about making selection but this research is completely based on empirical studies as well as benchmarking [8]. However, this research majorly considered several optimizers that focused on gradient as well as learning rate while comparing along with numerous workloads. Hence, the scientific progress has been improved with confidence in capability for generating empirical comparisons among various optimization algorithms. Thus, the study involves learning rate related optimizers such as follow the Regularized Layer (FTRL), nadam, adaGrad, adaMax, adadelta and Root Mean Square prop (RMSprop) in the CNN model. Although, the traditional optimizer experiences with finding are tuned prudently

whereas the adam and its adaptive gradient techniques may not underperform SGD or momentum. Subsequently, the optimizer sensitivity through hyperparameter protocols has been compared [9, 10]. Moreover, this study focuses on hyperparameter tuning protocol using optimizer in the DL model. Therefore, these optimizers involved with automatic hyperparameter tuning of LR in the CNN model which generate high accuracy of prediction in house pricing. Thus, the high accurate house pricing prediction assists the buyer and seller to view and understand the current frequency of users.

The remaining sections of the paper are organized as follows. Section 2 discusses about the back papers required for literature survey. The methods used for the research work is given in section 3. Section 4 explores the results obtained via experiments and its discussion. Finally, section 5 concludes the research findings.

2. Literature Review

There is various kind of modelling methods for house pricing are DL techniques, Geographically Weighted Regression (GWR), HPM and its variants. In the economics fields, the basic HMP is the first proposed pricing model to house price. The HPM presumption discuss about consumer pay to house which is not only for living spacing but also considered to influence factors like location benefits and an environment of neighborhood. Due to its efficiency and easiness in describing housing prices, HPM is broadly utilized in real estate studies [11]. The basic HPM with respect to the assumption in which the pattern doesn't modify its locations and not reflecting the difference of regional as well as variable local relationships that may result in altering modeling accuracy [12]. DL is an essential subfield of ML and ANN with respect to learning are the frequent method implemented. There are two well-known ANN architectures namely RNN and CNN in which the CNN involves convolution based Neural Network (NN) operations that consists of three different major layers such as input layer, hidden layers and output layers. Kim et al. have discussed about the hyperparameter combinations used in the Long Short Term Memory (LSTM) technique which utilized for generating prediction in house price that follow the ad hoc application but no specific method is used [13]. Lee and Park has introduces a tool for measuring the unpredictability of property valuation using Bayesian Neural Network (BNN) but the issues are not completely

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addressed. In order to outperform, Lie et al. have introduced pre-trained CNN technique for predicting the property price based on neighbor data samples [14, 15].

Liu have focused to optimize the weights that initially considered and back propagation NN threshold to estimate commercial real estate prices using bacterial chemotaxis PSO but it doesn't explore NN model hyperparameters [16]. Milunovich has discusses about forecast combination over various ML methods namely DLNN and kernel ridge regression for predicting Australian house pricing but not consider in individual model optimizations [17]. Štubňová et al. have established the ANN training model with various learning algorithms namely scaled conjugate gradient, Bayesian regulation and levenbergmarquart but not involves the architecture of optimization technique during hyperparameter levels to estimate residential property price [18]. Likewise, Zhao et al. have utilized a hybrid model which consists of CNN pre-trained model that involves predicting model to numeric features and also for extracting visual features from the images of property. In addition, the XGBoost component has performed regression model for predicting the prices of real estate [19].

Temur et al. have proposed a novel model by combining AutoRegression Integrated Moving Average (ARIMA) model with LSTM technique for developing better and improved prediction of house price in Turkey. The proposed model is evaluated through Error Rate (ERR) metrics like Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) as well as compared with other hybrid

model and determines that proposed model consume less ERR and high accurate in predicting house prices [20]. The secondhand home prices in Beijing, China have been forecasted by Yu et al. using the hybrid model with combination of CNN and LSTM network. The proposed model performance is evaluated through ERR metrics and compared with ARIMA model determines the proposed hybrid model performed better with less ERR [21]. To improve the house price forecasting, Ge have proposed a new technique that combines convolutional network in a learnable graph with LSTM network and graph CNN for capturing temporal and spatial features, community characteristics and economic factors [22].

3. Research Methodology

The purpose of this proposed CNN model with modified hidden layer is utilized for determining the house price by selecting various optimizer. The purpose of the optimizer is to initiate the better LR during training. Once the optimal hyperparameters tuning is not managed within the certain LR, then the LR is made to be decreased for improving the training model accuracy. There are several features provided as an input by users in the house sale price dataset shown in figure 1. The collected data involved with 22 variables and 7900 records that contributes the detailed information of number of rooms, bedrooms, register fees, commission, utility availability, type of building, date of build, Sq.Feet, and building sale price. These features are consider as dense layer in which certain layers have been altered and analyzed through CNN model.

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PRT ID	AREA	INT_SQFT	DATE SALE	DIST_MAIN ROAD	N_BED ROOM	N_BATH ROOM	N_ROOM	SALE COND	PARK FACIL	DATE BUILD	BUILD TYPE	UTILITY_AVAIL	STREET	MZONE	QS_ROOMS	QS_BATH ROOM	QS_BED ROOM	QS_OVERALL	REG_FEE in Rs.	COMMS in Rs.	SALES_PRICE in Rs.	
P03210	Karapakkam	1004	4/5/2011		131	1	1	3	AbNormal	Yes	15-05-1967	Commercial	AllPub	Paved	A	4	3.9	4.9	4.33	380000	144100	7600000
P09411	Anna Nagar	1886	19-12-2006		26	2	1	5	AbNormal	No	22-12-1995	Commercial	AllPub	Gravel	RH	4.9	4.2	2.5	3.765	760122	304049	21717770
P01812	Adyar	909	4/2/2012		70	1	1	3	AbNormal	Yes	9/2/1992	Commercial	ELO	Gravel	RL	4.1	3.8	2.2	3.09	421094	92114	13159000
P05346	Velachery	1835	13-03-2010		14	3	2	5	Family	No	18-03-1988	Others	NoSevr	Paved	I	4.7	3.9	3.6	4.01	356321	77042	9630290
P06210	Karapakkam	1226	5/10/2009		84	1	1	3	AbNormal	Yes	13-10-1979	Others	AllPub	Gravel	C	3	2.5	4.1	3.29	237000	74063	7406250
P00219	Chrompet	1220	11/9/2014		36	2	1	4	Partial	No	12/9/2009	Commercial	NoSeWa	No Access	RH	4.5	2.6	3.1	3.32	409027	198316	12394750
P09105	Chrompet	1167	5/4/2007		137	1	1	3	Partial	No	12/4/1979	Other	AllPub	No Access	RL	3.6	2.1	2.5	2.07	263122	33925	8488790
P09079	Velachery	1847	13-03-2006		176	3	2	5	Family	No	15-03-1996	Commercial	AllPub	Gravel	RM	2.4	4.5	2.1	3.26	604809	235204	10800250
P03377	Chrompet	771	6/4/2011		175	1	1	2	AdjLand	No	14-04-1977	Others	NoSevr	Paved	RM	2.9	3.7	4	3.25	257578	33226	8308970
P09623	Velachery	1635	22-06-2006		74	2	1	4	AbNormal	No	26-06-1991	Others	ELO	No Access	I	3.1	3.1	3.3	3.36	323346	121255	8083650
P09540	Chrompet	1203	19-10-2006		78	2	1	4	AdjLand	Yes	26-10-1978	Commercial	AllPub	No Access	RM	4	3.2	4.5	3.83	403326	11904	14933000
P07121	Chrompet	1034	16-02-2009		143	1	1	3	Partial	No	26-02-1972	Others	NoSevr	Gravel	RM	2.2	3.1	3.3	2.89	245693	141746	9449730
P05512	Chrompet	1196	11/2/2010		137	1	1	3	Family	No	16-02-1991	Others	NoSevr	No Access	RL	2.1	2.5	2.1	2.26	209554	35097	8774370
P09370	Adyar	1036	1/1/2007		83	1	1	3	Partial	Yes	7/1/1981	Others	NoSevr	Paved	RH	2.2	3.4	3.7	3.19	319141	37546	9306400
P04085	Velachery	1805	11/11/2010		137	3	2	5	Family	No	24-11-1956	Commercial	NoSevr	Paved	RM	4.8	2.2	4.9	3.66	619987	294194	15499680
P06328	Velachery	1868	12/9/2009		148	3	2	5	Family	No	14-09-2000	Commercial	NoSevr	Gravel	RH	3.8	3.8	3.1		597135	188669	15714080
P06039	Karapakkam	1639	4/11/2009		175	2	2	4	Normal Sale	Yes	9/11/1991	House	ELO	Gravel	I	2.3	3.2	4.8	3.57	283648	77904	8656000
P02016	Chrompet	796	25-12-2011		134	1	1	2	AdjLand	Yes	3/1/1975	Commercial	AllPub	No Access	RL	3.5	4.6	4.7	4.3	316464	130951	10912550
P08160	Adyar	1136	5/4/2008		69	1	1	3	Normal Sale	Yes	13-04-1978	Others	AllPub	Paved	A	4.6	2.6	2.9	3.35	323214	49725	8282750
P01372	Anna Nagar	1902	2/7/2012		168	2	1	5	Family	Yes	13-07-1970	Commercial	ELO	Paved	RL	4.5	4.9	4.9	4.76	740113	212032	21263240

Figure 1: Dataset for house sale price in different areas of Chennai



Once the data is collected and checked for missing data has been executed with missing value imputation. After missing imputation process, the data get preprocessed by labelEncoder for converting the object data type into integer or float data type to consider that as a

continuous variable and dropping the N_Room and DATE_BUILD_MONTH variables. Finally, the 18 input variable are preprocessed for scaling the all variable unit as unique using standardScaler. The dataset is split in term of 75% for train dataset as well as 25% for test dataset.

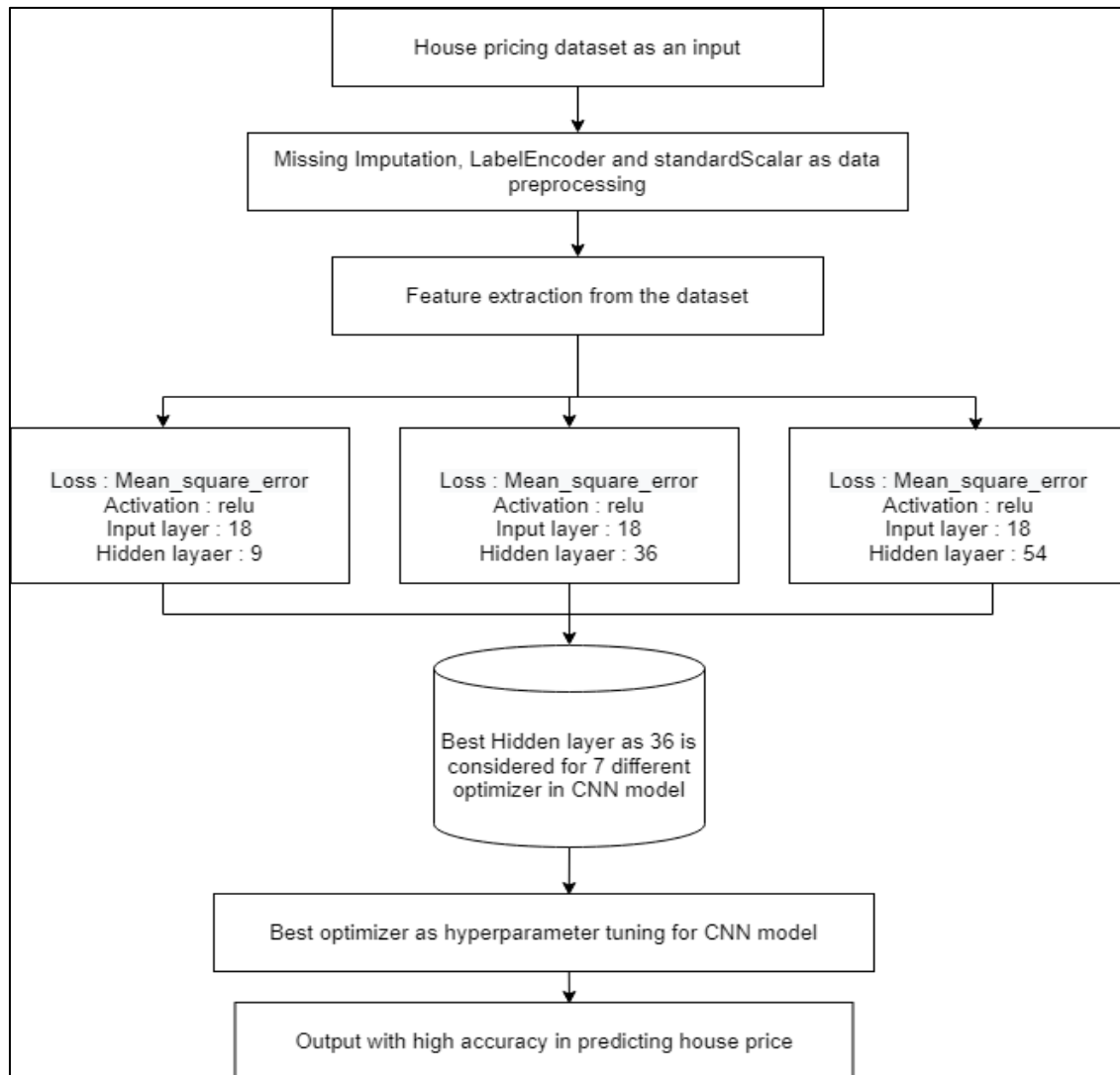


Figure 2: Architecture of hyperparameter tuning by optimizer in DL models

The model_1 is trained using CNN technique and set input layer shape as 18 whereas the hidden layer shape is made double as 36. This model has utilized “relu” as an activation and fit with batch size as 32 and 100 epochs are considered using adam optimizer. Similarly, model_2 is trained using CNN technique and set input layer shape as 18 in which the hidden layer shape is made half as 9. In the case of model_3, input layer shape is set as 18 in which the hidden layer shape is made thrice as 54 is shown in figure 2. These models have utilized “relu” as an

activation and fit with batch size as 32 and 100 epochs are considered using adam optimizer. The best hidden layer is considered for other optimizers like Follow The Regularized Layer (FTRL), nadam, adaGrad, adaMax, adadelta and Root Mean Square prop (RMSprop). The LR is set to 0.1 that determines by looking at the learning curve when the objective function is plotted as a function of frequency. Since the problem falls under the category of binary classification, cross entropy is used to calculate the loss whereas the epoch is set to 100 and the batch size is 32.



Table 1: Sequence of Various hidden layer of CNN model

Sequential Nos.	Layer type	Layer Nos.	Output Shape	Params
Sequential 1	Dense	Dense_6	(None, 18)	342
	Dense	Dense_7	(None, 36)	684
	Dense	Dense_8	(None, 36)	1332
	Dense	Dense_9	(None, 1)	37
Sequential 2	Dense	Dense_10	(None, 18)	342
	Dense	Dense_11	(None, 9)	171
	Dense	Dense_12	(None, 9)	90
	Dense	Dense_13	(None, 1)	10
Sequential 3	Dense	Dense_18	(None, 18)	342
	Dense	Dense_19	(None, 54)	1026
	Dense	Dense_20	(None, 54)	2970
	Dense	Dense_21	(None, 1)	55

According to the Table 1, the different sequence of hidden layer with their overall params has been determined. The sequential 1 with total params is 2395 followed by sequential 2 and sequential 3 as 613 and 4393 correspondingly. Among the three sequences, sequential 1 has preferred to be better hidden layer in determining high accuracy with adam optimizer. Similarly, the sequential 1 is considered for various optimizers such as FTRL, nadam, adaGrad, adaMax, adadelta and RMSprop.

The Rectified Linear unit function is known as Relu which perform as an activation function has become the major benefits that all neurons are not activated at a time. Relu function assess the zero value or make it as a deactivated neuron for the neuron with negative value which create the network as an inadequate as well as performing efficient calculation. In the case of negative side graph, the gradient value has become zero that may signify at backpropagation in which the neurons have been terminated and activation is not obtained. Moreover, the softmax function is performed as sigmoid extension function which utilized to maintain multi-class issues and get mapped an output value with in the range of 0 to 1. This is generally applicable for classifier's output layer in which no standard rules are applicable to choose an activation function. The issues properties have the capability in generating a best option to rapid convergence network. According to this research, Relu activation function is considered in the hidden dense type layers to obtain improved accuracy.

Optimizer is the process which assists in minimizing the network error which is essential to improve the model accuracy. There are several optimizer variants involved with learning rate automate hyperparameter tuning with adaGrad, adadelta, adam, nadam, adaMax, FTRL and RMSprop.

According to the saddle point maintenance, the optimizer used are adam, adaGrad, adadelta and adam have been considered majorly. The main drawback of the AdaGrad optimizer is that which reduces the model's capacity to learn by making the learning rate with infinitesimally small. There are two mentioned optimizers namely RMSprop and AdaDelta, are independently created for addressing the issues with AdaGrad. However, the AdaDelta and RMSprop function are similar in which the only different is that AdaDelta does not call for constant initial learning rate. Adam is a different type of optimizer that combines the beneficial aspects of RMSprop and Adadelta. Each parameter's LR is calculated in which Adam has been considered best option in general as it outperforms RMSprop and Adadelta but RMSprop shows better outcome than adam which selected as an top optimizer in the CNN model.

Most crucial factors used to fine-tune the models is LR which updates the network weights to reduce error. Model performance get decreased, if the LR is set too low or too high in which the LR may result with minimal network weight upgrades and slow down training whereas a high LR has resulted in differing error behavior. In actual training, a high LR is used before because random weights at the beginning are beyond ideal and LR might well fine-tune the network weights by lowering their value during training. The learning process may begin with a large value, such as 0.1, and move on to smaller values, such as 0.01, 0.001, etc. The quantity of epochs indicates how many times the training dataset is traversed whereas each epoch suggests that the training sample has the ability to update the internal model parameters. One or more batches might be present which is possible for there to be



zero or infinitely many epochs. In most cases, hundreds or thousands of epochs are picked which enables the network to adequately lower the error. However, the learning curves of error and accurateness to select the best epoch value. Hence, the curves can be used to identify whether the model has learned too much, too little, or is adequately prepared for training.

Accordingly, the CNN model has adopted adaGrad, adam, adaMax, adadelta, nadam, FTRL and RMSprop optimizer which are applicable and the respective ERR as well as accuracy is evaluated in the next session of this paper. The algorithm of optimizer implementation over CNN model is explained below

Optimizer algorithm in CNN technique

Step 1: CNN technique with sequential classification of hidden layer is initialized.

Step 2: The convolution layer process with dense type and pooling process with relu activation function is applied.

Step 3: Converting of non-linear vector into continuous linear vector by applying flattening process.

Step 4: The model is built with the three combinations of Input layer and output layers. The sequential 1 with twice the input layer, sequential 2 with half of input layer and sequential 3 with thrice the input layer are executed.

Step 5: Compiling the loss function with "Root Mean Square" and seven different optimizer layers in CNN model.

Step 6: The values are made to fit the CNN and the train data and test data sets are generated.

Step 7: Finally, Run the CNN model with batch size 32 and for 100 epochs.

The CNN can efficiently extract the complex characteristics among the relevant variables of housing, and the optimizer selection is essential in improving the prediction of the model which efficiently reflects in aggregating the learning rate training to increase the accuracy of predicting house price by improving the CNN model accuracy.

4. Results and Discussion

This research is executed with i5-7400 processor, GTX1050 GPU at 3 GHz whereas the system includes 8 GB RAM with 64 bits. The script utilized for training the model with python programming in googlecolab as open source using Tensorflow and sklearn library. The models have been evaluated with various parameters like input layer, hidden layer optimizer function, activation function, LR, batch size and epochs number involved in CNN models. The optimizer algorithm optimizes the followed hyperparameters namely batch size, LR, optimization algorithm, model architecture, and activation function. However, the selection of hyperparameter tuning to each optimizer is the major empirical method selections of optimizers. Hence, it requires an assumption that named similar hyperparameters which need a similar values among these optimizers that are not generally true. The error rate metric value and accuracy findings through R2 and adjusted R2 for various optimizer in CNN model is shown in table 1.

Figure 3 shows that maximum frequency of user with sales price of 10.1 Million is identified in the chrompet area with 24% followed by karapakkam with 19% which is 7.0 Million. The least frequency is obtained in the area of T.Nagar with 8% whereas the sales price is high in that area.

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Table 1: Error rate and accuracy values for different optimizers

Sl.No	Optimizer Type	RMSLE	R2	Adjusted R2
1	Adam	14.051	0.8846	0.8834
2	RMSProp	14.0483	0.8852	0.8841
3	Adadelta	16.2515	-0.84074	-0.85036
4	AdaGrad	16.2513	-0.84032	-0.84996
5	AdaMax	14.1619	0.856	0.8545
6	Nadam	14.0571	0.8832	0.882
7	FTRL	16.2513	-0.84042	-0.85004



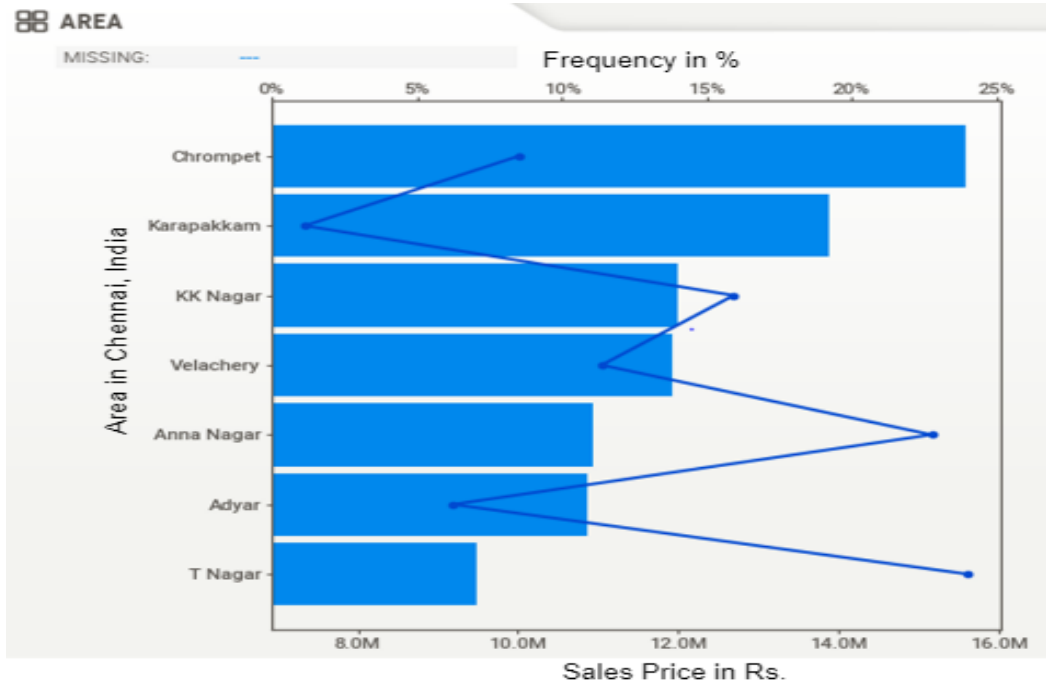


Figure 3: Sales price and frequency of user for various areas in Chennai

Figure 4 shows that maximum frequency of user in commission after sales is nearly 125k is identified with 26% within the sales price range between 10.0Million to 12.0 million followed by commission after sales nearly 90k with 25% in which the sales

price with range between 10.0Million to 12.0 million. The least frequency is 1% obtained in the high commission after sales for approximately 480k which lies in the sales price range between 1458 18.0Million to 20.0 million.

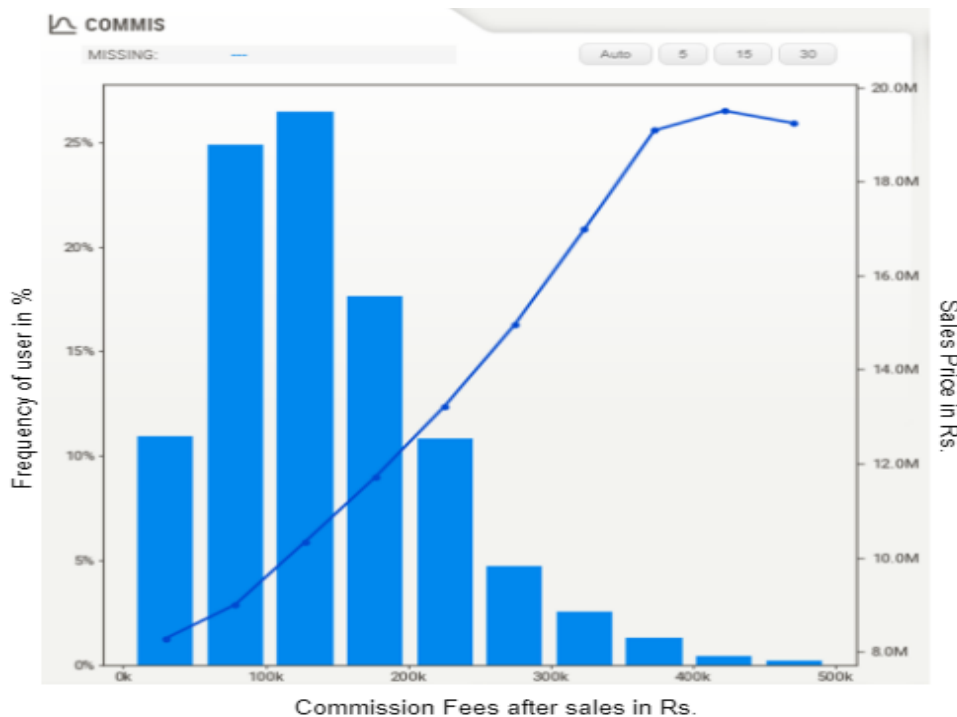


Figure 4: Commission fees and frequency of user for various house sales prices



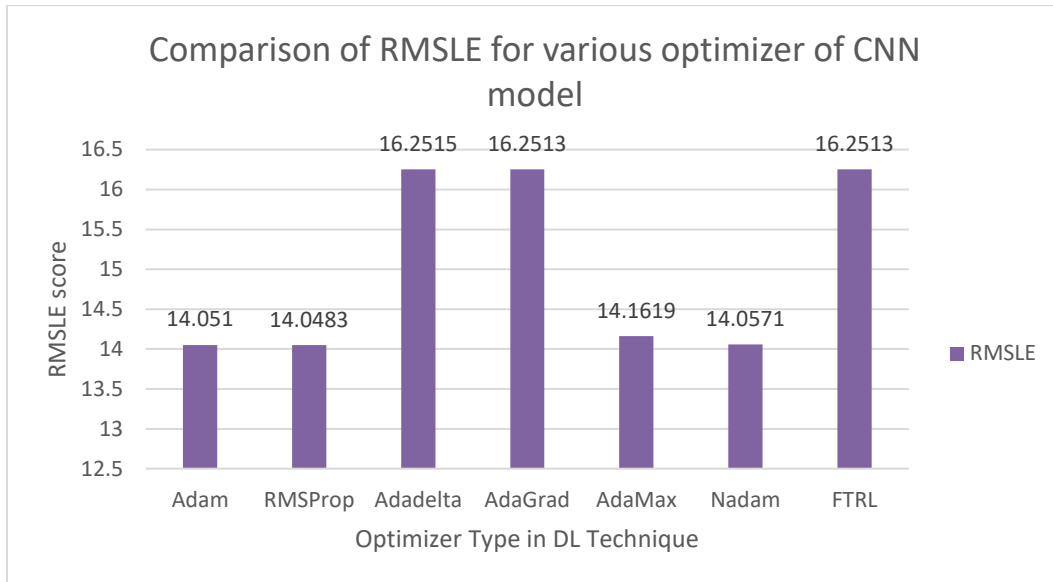


Figure 5: Comparison of RMSLE for various optimizer used in CNN model

Figure 5 shows the values obtained using different optimizers like Adam, RMSprop, nadam, adagrad, etc. in which the RMSprop optimizer produced better result compared to Adam with least Root Mean Square Log Error (RMSLE) of 14.048. The ERR of RMSprop is comparatively lesser while compared to other optimizer in which the adam is slightly

higher than adam. The LR has increased and it obtain with significant steps over horizontal direction that converges faster. The RMS loss function has quantified the similarity among predicted output provided by the CNN through forward propagation as well as particular ground truth labels.

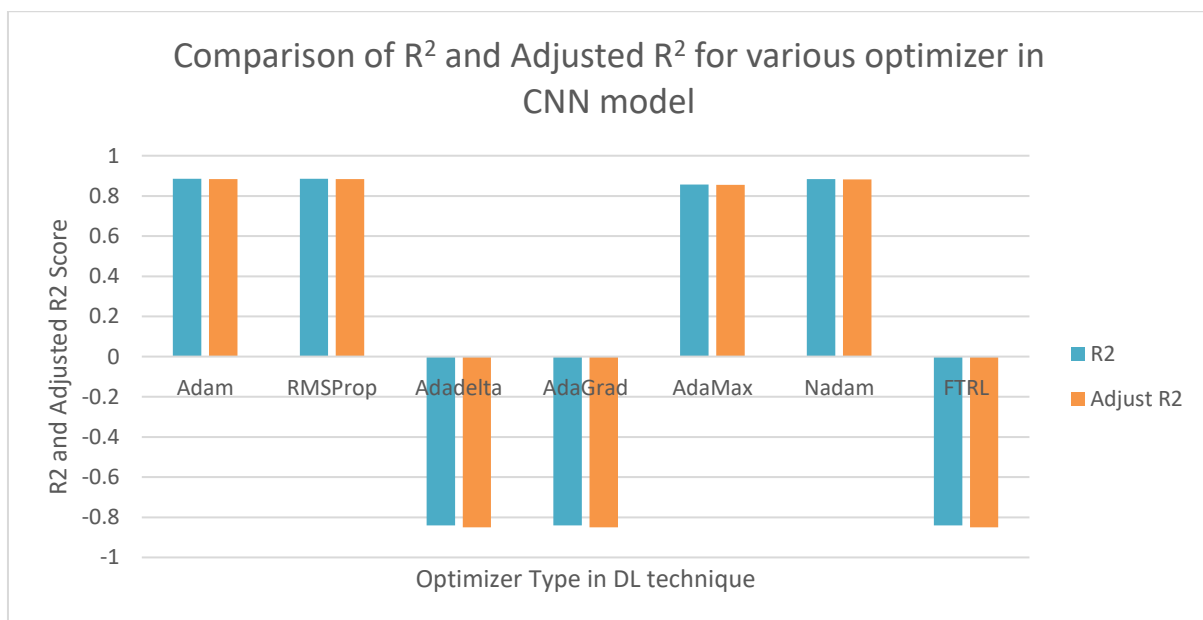


Figure 6: Comparison of R² and adjusted R² for various optimizer used in CNN model

Figure 6 shows the R2 and adjusted R2 values that accomplished by various optimizers such as Adam, RMSprop, nadam, adagrad, etc. in which the RMSprop optimizer produced better result compared to Adam with high accuracy of R2 as 0.8852 and adjusted R2 as 0.8841. The accuracy of

RMSprop is comparatively higher while compared to other optimizer in which the adam is slightly lesser than RMSprop. The LR has increased and it obtains with significant steps over horizontal direction that converges faster. Thus, the proposed CNN model with RMSprop is utilized for better



house price prediction has been determined.

5. Conclusions

The house price prediction for application is the major task that required awareness into data combination with powerful DL algorithms. This proposed model utilized the essential data through user frequency in all over areas in the respective state or countries which propose an attention through features of house pricing detail related to all characteristics. These features can assign weights based on several features and records in the house pricing datasets. However, the end to end model is designed through DL method with hyperparameter tuning protocol as an optimizer sensitivity. Hence, the optimizer associated with LR hyperparameter has assisted to reduce the error has helped to improve the model accuracy. The comparison is majorly focused for ensuring the labeled data set with default optimizer as Adam that considered as an adaptive learning algorithm which provides best model performance. The optimizer model is evaluated through ERR metrics like RMSLE, R2 and adjusted R2 in which the RMSprop optimizer generate better results while compared to other optimizers. The RMSLE metrics for RMSprop considered least ERR with 14.048 and high accuracy in R2 and adjusted R2 as 0.8852 and 0.8841 corresponding while compared in the CNN model. In future, the hyperparameter tuning over ML methods is implemented by initializing the parameter weight through randomizedsearchCV technique for improving the accuracy of predicting house price.

References

- Poursaeed, O., Matera, T., and Belongie, S. "Vision-based real estate price estimation", *Machine Vision and Applications*, 2018, Vol. 29, No. 4, pp. 667–676.
- Fan, C., Cui, Z., and Zhong, X. "House prices prediction with machine learning algorithms", *Proceedings of the 10th International Conference on Machine Learning and Computing*, 2018, pp. 6–10.
- Peter NJ, Okagbue HI, Obasi ECM, Akinola AO. "Review on the application of artificial neural networks in real estate valuation", *International Journal of Advanced Trends in Computer Science and Engineering*, 2020, 9(3); pp. 2918–2925.
- Varma A, Sarma A, Doshi S, Nair R. "House price prediction using machine learning and neural networks", *Proceedings of the International Conference on Inventive Communication and Computational Technologies*, 2019, ICICCT 2018, Coimbatore, India, pp. 1936–1939.
- Ho WKO, Tang B-S, Wong SW. "Predicting property prices with machine learning algorithms", *Journal of Property Research*, 2020, 38(1):pp. 1–23.
- Srinivas, S., Sarvadevabhatla, R. K., Mopuri, K. R., Prabhu, N., Kruthiventi, S. S., & Babu, R. V. 2016, "A taxonomy of deep convolutional neural nets for computer vision".
- ArthaAndriyanto, AntoniWibowo NS NorhaslindaZainalAbidin "Sectoral Stock Prediction Using Convolutional Neural Networks with Candlestick Patterns as input Images", *International Journal of Emerging Trends in Engineering Research* 8, 2020, pp. 2249-2252.
- Schneider, F., Balles, L., and Hennig, P. DeepOBS: "a deep learning optimizer benchmark suite". arXiv preprint, 2019, arXiv:1903.05499.
- Wilson, A. C., Roelofs, R., Stern, M., Srebro, N., and Recht, B. "The marginal value of adaptive gradient methods in machine learning. In *Advances in Neural Information Processing Systems*", 2017, 30, pp. 4148–4158. Curran Associates, Inc.
- Balles, L. and Hennig, P. "Dissecting Adam: The sign, magnitude and variance of stochastic gradients", arXiv e-prints, art.2017, arXiv:1705.07774.
- Liebelt, V.; Bartke, S.; Schwarz, N. "Hedonic pricing analysis of the influence of urban green spaces onto residential prices: The case of Leipzig", Germany. *Eur. Plan. Stud.* 2018, 26, pp. 133–157.
- Cajias, M.; Ertl, S. "Spatial effects and non-linearity in hedonic modeling: Will large data sets change our assumptions", *J. Prop. Invest. Financ.* 2018, 36, pp. 32–49.
- Kim H, Kwon Y, Choi Y. "Assessing the impact of public rental housing on the housing prices in proximity: based on the regional and local level of price prediction models using long shortterm memory (LSTM). *Sustainability*", 2020, 12(18):7520.
- Lee C, Park KK. "Representing uncertainty in property valuation through a bayesian deep learning approach. *Real Estate Management and Valuation*", 2020, 28(4): pp.15–23.
- Liu R, Liu Y, Yan Y, Wang J. "Iterative deep neighborhood: a deep learning model which involves both input data points and their neighbors", *Computational Intelligence and Neuroscience* 2020 : pp.1–10.
- Liu Y. "A commercial real estate price evaluation model based on GT-BCPSO-BP neural network", *International Journal of Applied Decision Sciences*, 2017, 10(4): pp.335–346.
- Milunovich G. "Forecasting australia's real house price index: a comparison of time series and machine learning methods. *Journal of Forecasting*", 2020, 39(7): pp.1098–1118.
- Štubňová M, Urbaníková M, Hudáková J, Papcunová V. "Estimation of residential property market price: comparison of artificial neural networks and hedonic pricing model. *Emerging Science Journal*", 2020, 4(6):pp.530–538.
- Zhao Y, Chetty G, Tran D. "Deep learning with XGBoost for real estate appraisal. In": 2019 IEEE Symposium Series on Computational Intelligence, SSCI, 2019, Piscataway: IEEE, pp.1396–1401.
- A. S. Temür, M. Akgün, and G. Temür, "Predicting housing sales in Turkey using ARIMA, LSTM and hybrid models," *J. Bus. Econ. Manage*, 2019, vol. 20, no. 5, pp. 920–938.
- L. Yu, C. Jiao, H. Xin, Y. Wang, and K. Wang, "Prediction on housing price based on deep learning", *Int. J. Comput. Inf. Eng.*, 2018, vol. 12, no. 2, pp. 90–99.
- C. Ge, "A LSTM and graph CNN combined network for community house price forecasting", *Proc. Of 20th IEEE Int. Conf. on Mobile Data Manage*, 2019, pp. 393–394.

