CNN predicts house or apartment rent more accurately than Naive Bayes does in major cities.

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ABSTRACT
Aim: The aim of this research article is to improve the accuracy rate in Novel Rent Prediction of house or flat rent in metro cities by using Convolutional Neural Network (CNN) in comparison with Decision Tree (D-Tree) Classification . **Materials & Methods:** The data set in this paper utilizes the publicly available Kaggle data set for Novel Rent Prediction of house or flat rent in metro cities. The sample size of Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate was sample 80 (Group 1=40 and Group 2 =40) and calculation is performed utilizing G-power 80% with alpha and beta qualities are 0.05, 0.2 with a confidence interval at 95%. The prediction of house or flat rent in metro cities with improved accuracy rate is performed by Convolutional Neural Network (CNN) whereas number of samples (N=10) and Decision Tree (D-Tree) where number of samples (N=10). **Results:** The Convolutional Neural Network (CNN) classification has 96.32 higher accuracy rates when compared to the accuracy rate of Decision Tree (D-Tree) is 94.15. There exists a statistically significant difference between the two groups ($p=0.0300$; $p<0.05$) with confidence interval 95%. **Conclusion:** Convolutional Neural Network (CNN) provides better outcomes in accuracy rate when compared to Decision Tree (D-Tree) for Novel Rent Prediction of house or flat rent in metro cities.
Keywords: machine Learning, Rent, Metro cities, Novel Convolutional Neural Network, Decision Tree, Prediction.

INTRODUCTION

House rent estimation has been broadly studied a lot as described in(Valadez 2011; Xu 2017). Establishing a housing rent estimating model can greatly help the formulation of housing prices and improve the accuracy of estimation of future real estate policies(Meidani, Zabihi, and Ashena 2011; Quigley 2002). The pricing of house rent not only depends on the size of the property and no. of rooms, but also on the neighborhoods like transport facility, banks, schools or colleges, shops etc. When a person buys a home, they consider structural features, working accessibility, neighborhood services. Hence, a house price Novel Rent Prediction system is invented to improve estimation of house prices (Oliphant 2007). This study presents a house rent Novel Rent Prediction using a novel convolutional neural network (CNN) algorithm(Zhan et al. 2020). Machine learning plays a major role in many of the application areas like image detection, spam reorganization, economics, banking sectors, normal speech command, product recommendation and medical diagnosis (Cao, Yang, and Others 2018).

Recently, a lot of interesting work has been done in the area of applying machine learning and deep learning algorithms for analyzing house rent patterns and predicting housing prices. IEEE Explore published 89 research papers, and Google Scholar found 119 articles. The paper proposed by Neelam Shinde, Kiran Gawande(Shinde and Gawande 2018) surveyed to predict a continuous target value, using algorithms Logistic Regression, Support Vector Machine, Lasso Regression Technique and Decision Tree are used to build a predictive model. It was found that the Decision Tree had the best accuracy of 84% approx. They tried to implement the problem of Regression using the Classification Algorithm which was successful. Guanglan Wei used the Markov chain to study housing price behaviors for the city of Kunming(Wang, Chen, and Li 2007), but with some influential factors ignored. In addition, Shengping Sin provided an algorithm based on Random Forest with a more satisfied result than the ARMA model(Xue et al. 2020). Similar works also included BP neural network(Jiang and Shen 2019) and GM model etc. Kumar experiments with different machine learning algorithms such as Linear regression, Decision Tree, and Nearest Neighbor(Kumar et al. 2015). He concludes that Naïve Bayes is consistent for unequal distribution frequency and Decision Tree is the most consistent classification for equal frequency distributions. One of the most popular ways to predict house pricing through machine learning is the use of Linear Regression as the model contains many features affecting the price(Cao, Yang, and Others 2018). An approach to the use of Artificial Neural Network was used to predict the house prices in New Zealand(Limsombunchai 2004). It proved to be a daunting task as the multiple features required powerful calculations from algorithms, but the results were promising. The most cited article was(Liu 2013), in Google scholar explore with 58 citations and 1134full text views.(Bhavikatti et al. 2021; Karobari et al. 2021; Shanmugam et al. 2021; Sawant et al. 2021; Muthukrishnan 2021; Preethi et al. 2021; Karthigadevi et al. 2021; Bhanu Teja et al. 2021; Veerasimman et al. 2021; Baskar et al. 2021)

The Limitation of the existing method for house rent Novel Rent Prediction is their inability to accurately predict highly dynamic and fast changing patterns in house rent movement. The current work attempts to address this shortcoming by exploiting the power of novel Convolutional Neural Networks in learning the past behavior of house rent price movements and making a highly accurate forecast for the future behavior of the house rent price. The aim of the paper is that the model based on CNN can effectively identify the changing trend of housing prices and predict it which can provide valuable reference for house rent forecasts.

MATERIALS AND METHODS

This work was carried out in the laboratory of Artificial Intelligence, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, chennai,India. The dataset is the prices and features of residential houses rent from 2016 to 2019 collected from some of the Housing Firms, a few web portals like nobroker.com, magicbricks.com(Liu 2013). This dataset consists of 60 house features and 1100 houses with rent prices. The dataset consists of features in various formats. It has numerical data such as prices and numbers of bathrooms/bedrooms/living rooms, as well as categorical features such as zone classification for sale, which can be Agricultural, Residential High Density, Residential Low Density, Residential Low Density Park, etc. Sample size was calculated using previous literature(Otero Gomez et al. 2020). The database is divided by the amount of 75% training and 25% testing. Group 1 was a Decision Tree (D-Tree)algorithm and Group 2 was a novel Convolutional Neural Network (CNN) algorithm. In this work two groups are taken and 10 samples for each group, total samples considered are 20. The output is obtained by using Python software for the Novel Rent Prediction of house rent prices. The calculation is performed utilizing G-power 0.8 with alpha and beta qualities 0.05, 0.2 with a confidence interval at 95%.

The sample group 1 is the Decision Tree (D-Tree) algorithm is a supervised learning algorithm that works for both discrete and continuous variables. The steps involved in the implementation of the D-Tree algorithm are described as follows.

Decision Tree Regression, as the name suggests, uses tree-like structure to build regression and classification models. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. A decision node has two or more branches, each representing values for the attribute tested. Leaf node represents a decision on the numerical target. The topmost decision node in a tree which corresponds to the best predictor called root node. Decision trees can handle both categorical and numerical data. The Decision tree output for classifying the availability of houses has discrete binary values like Yes or No. The output of the Decision tree Regression used for house price Novel Rent Prediction is a continuous one.

The continuous values (Prices) are predicted with the help of a decision tree regression model. Once the Decision Tree is formed, new instances can be classified easily by tracing the tree from root to leaf node. Classification through the Decision Tree does not require much computation. Decision Trees are capable of handling both continuous and Categorical type of attributes. To avoid generation of meaningless and unwanted rules in Decision Trees, trees should not be deeper which results in over fitting. Such a tree with over fitting works more accurately with training data and less accurate with test data. Pre pruning and Post pruning are the techniques used in Decision Tree to reduce the size of the trees and avoid overfitting. In Post Pruning the Decision Tree branches and hence the level (depth) of the tree are reduced after completely building the tree. In Pre Pruning, care is taken to avoid overfitting while building the tree itself.

The sample preparation group 2 is the novel convolutional neural network (CNN), which is a multi-layered feed-forward neural network, made by stacking many hidden layers on top of each other in sequence. The experimental results show that the proposed CNN method has achieved better accuracy results.

Pseudocode for Decision Tree (D-Tree) Classifier

```
GenDecTree(Sample S, Features F)
Steps:
1. Ifstopping_condition (S,F) = true then
        a. Leaf = createNode()
        b. leafLabel = classify(s)
        C. return leaf
2. root = createNode()
3. root.test_condition =findBestSpilt(S,F)
4. V = {v|v a possible outcomecfroot.test_condi
5. For each value v € V:
        a. S = {s | root.test_condition(s) = v and
        b. Child TreeGrowth (S,F);
        C. Add child as descent of root and labe
6.   return root
```

Novel convolutional neural network is a feed-forward neural network. Like the traditional architecture of a neural network including input layers, hidden layers and output layers, convolutional neural networks also contain these features and the input of the layer of convolution are the output of the previous layer of convolution or pooling. Of course, they still have some unique features such as pooling layers, full connection layers, etc. The number of hidden layers in a convolutional neural network is more than that in a traditional neural network, which, to some extent, shows the capability of the neural network. The more the hidden layers are, the higher feature it can extract and recognize from the input. CNN has achieved good results in time series problems. When convolution kernels that share the same weights are applied to local signals at different time segments, a type of translation invariance is obtained. Convolution layer is the core of CNN. The convolution kernel, also called filter, could be considered as a small window that contains learned parameters as a matrix form. This filter slides all over the input data to capture the local information by applying the convolution operation on each patch. Different local information by applying different convolution kernels would be combined to generate the global information. Pooling layer is added between continuous convolution layers in one CNN structure. It is designed to gradually reduce the amount of data and parameters, which could help to avoid overfitting to some extent. The pooling layer utilizes a small sliding window which is similar to the convolution layer. The convolved features of a specific area are compressed into the maximum value or the mean value of that area. Fully connected layer is applied after several convolution layers and pooling layers to obtain the Novel Rent Prediction results or classification results. The latent features through dimensionality reduction and feature extraction would be learned well with a fully connected layer.

Pseudocode for Novel convolutional neural network

Step 1: Find average of independent variables and image quantity in libraries.
Step 2: Observe error from CNN algorithm i.e.(observed bytes of image)-(predicted the compressed bytes) or vice versa this is stored as a residual.
Step 3: Now construct a Table using dependent variables which leads to predict the compressed quantity of an image.
Step 4: By concatenating two algorithms which makes a new prediction of individual values from the training data .
Step 5: Now add average value column calculated compressed image in first step with final outcome of CNN image which will give final predicted bytes (or) Accuracy.

Statistical Analysis

The output is obtained by using Python software(Oliphant 2007). To train these datasets, required a monitor with resolution of 1024×768 pixels (7th gen, i5, 4 8GB RAM, 500 GB HDD), and Python software with required library functions and tool functions. For statistical implementation, the software tool used here is IBM SPSS(Frey 2017). The independent sample t test was performed to find the mean, standard deviation and the standard error mean statistical significance between the groups, and then comparison of the two groups with the SPSS software will give the accurate values for the two different s which will be utilized with the graph to calculate the significant value with maximum accuracy value (96.32%), mean value (95%) and standard deviation value (0.21122s). Dependent variables are accuracy and independent variables are image size.

RESULTS

Figure 1 shows the simple bar graph for Decision Tree (D-Tree) Classifier accuracy rate is compared with Novel Convolutional Neural Network (CNN) Classifier. The Convolutional Neural Network (CNN) Classifier is higher in terms of accuracy rate 96.32 when compared with Decision Tree (D-Tree) Classifier 94.15. Variable results with its standard deviation ranging from 80 lower to 90 higher Decision Tree (D-Tree) Classifier where Convolutional Neural Network (CNN) Classifier standard deviation ranging from 90 lower to 100 higher. There is a significant difference between Decision Tree (D-Tree) Classifier and Convolutional Neural Network (CNN) Classifier ($p<0.05$ Independent sample test). X-axis: Convolutional Neural Network (CNN) Classifier accuracy rate vs Decision Tree (D-Tree) Classifier Y-axis: Median of accuracy rate, for identification of keywords ± 1 SD with 95 % CI.

Table.1 shows the Evaluation Metrics of Comparison of Decision Tree (D-Tree) and Convolutional Neural Network (CNN) Classifier. The accuracy rate of Decision Tree (D-Tree) is 94.15 and Convolutional Neural Network (CNN) has 96.32. In all aspects of parameters Convolutional Neural Network (CNN) provides better performance compared with the Decision Tree (D-Tree) of Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate.

Table.2 The statistical calculation such as Mean, standard deviation and standard error Median for Decision Tree (D-Tree) and Convolutional Neural Network (CNN). The accuracy rate parameter used in the t-test. The mean accuracy rate of Decision Tree (D-Tree) is 94.15 and Convolutional Neural Network (CNN) is 96.32. The mean and Standard Deviation of Decision Tree (D-Tree) is 91.20,1.2365 and Convolutional Neural Network (CNN) is 92.40,0.21122. The Standard Error Median of Decision Tree (D-Tree) is 0.87363 and Convolutional Neural Network (CNN) is 0.1289.

Table.3 displays the statistical calculations for independent samples test between Decision Tree (D-Tree) and Convolutional Neural Network (CNN). TThe statistical calculations for independent samples test between Decision Tree (D-Tree) and Convolutional Neural Network (CNN). There exists a statistically significant difference between the two groups ($p=0.0300$; $p<0.05$) with confidence interval 95%. This independent sample test for comparison of Decision Tree (D-Tree) and Novel Convolutional Neural Network (CNN) consists of significance as 0.000, significance (2-tailed), Mean difference(11.89388,11.0123), standard error difference (0.76734,0.12421, and lower (11.73674,10.12353)and upper (13.78374,12.02343) interval difference.

DISCUSSION

This study proposes an integrated CNN model to predict the house rent in metro cities. To verify the effectiveness of the proposed model, we compare its performance to D-Tree and CNN models without optimization users to predict the availability of houses in the city and also to predict the prices of the houses. Two algorithms like decision tree regression and CNN were used in predicting the prices of the houses. Comparatively the performance CNN is found to be better than the decision tree regression in predicting the house prices. Performance of convolutional neural networks is better than the decision tree model for predicting the prices of houses. The developed model can be used to predict the availability and prices of houses for any new record as per the user constraints. The performance of CNN deep learning model was found to have far too superior to that of the machine learning based predictive model.There exists a statistically significant difference between the two groups ($p=0.0300$; $p<0.05$) with confidence interval 95%.

The study has conclusively elicited the fact that CNN models have much higher capability in extracting and learning the features of a training dataset than their corresponding machine learning counterparts. Four effective measures that have been used in this study are based on confusion matrix output, which are True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Accuracy is the ratio of the number of cases which are correctly classified to the total number of cases expressed as a percentage. Specificity is the ratio of the true negatives (correctly identified “0” s) to the total number of negatives in the test dataset expressed as a percentage. Sensitivity is the ratio of the number of true positives to the sum of the true positive cases and false positive cases expressed as a percentage.Various methods have been proposed in the literature studies to predict the house rent over the past few years. Fan et al(Fan, Ong, and Koh 2006) has utilized the decision tree approach for finding the resale prices of houses based on their significant characteristics. In this paper, hedonic based regression method is employed for identifying the relationship between the prices of the houses and their significant characteristics. Ong et al.(Ong, Ho, and Lim 2003) and Berry et al.(Berry et al. 2003) have also used hedonic based regression for house Novel Rent Prediction based on significant characteristics and obtained an accuracy rate of 94.8%. Shinde and Gawande(Shinde and Gawande 2018), predicted the sale price of the houses using various machine learning algorithms like, lasso, SVR, Logistic regression and decision tree and compared the accuracy. Alfiyatin et al.(Nur et al. 2017) has modeled a system for house price prediction using Regression and Particle Swarm Optimization (PSO). In this paper, it has been proved that the house price Novel Rent Prediction accuracy is improved by combining PSO with regression. Timothy C. Au(Au 2018) addressed the absent level problems in Random Forests, Decision Trees, and Categorical Predictors and achieved an accuracy of 91.5%.

A limitation of using the CNN is the difficultly in interpretation on intermediate features inside its architecture. In future the dataset can be prepared with more features and advanced deep learning techniques can be used for constructing the house price Novel Rent Prediction model.

CONCLUSION

The proposed model exhibits the Decision Tree (D-Tree) and Convolutional Neural Network (CNN), in which the Convolutional Neural Network (CNN) has the highest values. The accuracy Rate of Convolutional Neural Network (CNN) is 96.32 is higher compared with Decision Tree (D-Tree) that has an accuracy rate of 94.15 in analysis of Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate.

DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript

Authors Contributions

Author KSR was involved in data collection, data analysis & manuscript writing. Author TV was involved in conceptualization, data validation, and critical review of manuscripts.

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TABLES AND FIGURES

Table 1. Comparison of Decision Tree (D-Tree) and Convolutional Neural Network (CNN) Classifier for Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate. The accuracy rate of Decision Tree (D-Tree) is 94.15 and Convolutional Neural Network (CNN) has 96.32.

SI.No.	**Test Size**	**Novel Convolutional Neural Network (CNN) Classifier**	Decision Tree (D-Tree) Classifier
1	550	92.45	90.10
2	600	93.00	90.00
3	650	93.56	91.00
4	700	94.21	91.52
5	750	94.02	92.03
6	800	94.56	93.00
7	850	95.05	92.52
8	900	95.56	91.32
9	950	95.12	93.00

10	990	96.32	94.15

Table 2. The statistical calculation such as Mean, standard deviation and standard error Median for Decision Tree (D-Tree) and Convolutional Neural Network (CNN). The accuracy rate parameter used in the t-test. The mean accuracy rate of Decision Tree (D-Tree) is 94.15 and Convolutional Neural Network (CNN) is 96.32. The mean and Standard Deviation of Decision Tree (D-Tree) is 91.20,1.2365 and Convolutional Neural Network (CNN) is 92.40,0.21122. The Standard Error Median of Decision Tree (D-Tree) is 0.87363 and Convolutional Neural Network (CNN) is 0.1289.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
ACCURACY	CONVOLUTIONAL NEURAL NETWORK (CNN)	10	92.40	0.21122	0.1289
	DECISION TREE (D-TREE)	10	91.20	1.2365	0.87363

Table 3: The statistical calculations for independent samples test between Decision Tree (D-Tree) and Convolutional Neural Network (CNN). There exists a statistically significant difference between the two groups (p=0.0300; p<0.05) with confidence interval 95%. This independent sample test for comparison of Decision Tree (D-Tree) and Novel Convolutional Neural Network (CNN) consists of significance as 0.000, significance (2-tailed), Mean difference(11.89388,11.0123), standard error difference (0.76734,0.12421, and lower (11.73674,10.12353)and upper (13.78374,12.02343) interval difference.

Group		Levene's Test for Equality of Variances		t-test for Equality of Medians						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy	Equal variances assumed	0.878	0.0300	17.234	18	.000	11.89383	0.76734	11.73674	13.78374
	Equal variances not assumed			17.234	12.8273	.000	11.01231	0.12421	10.12353	12.02343

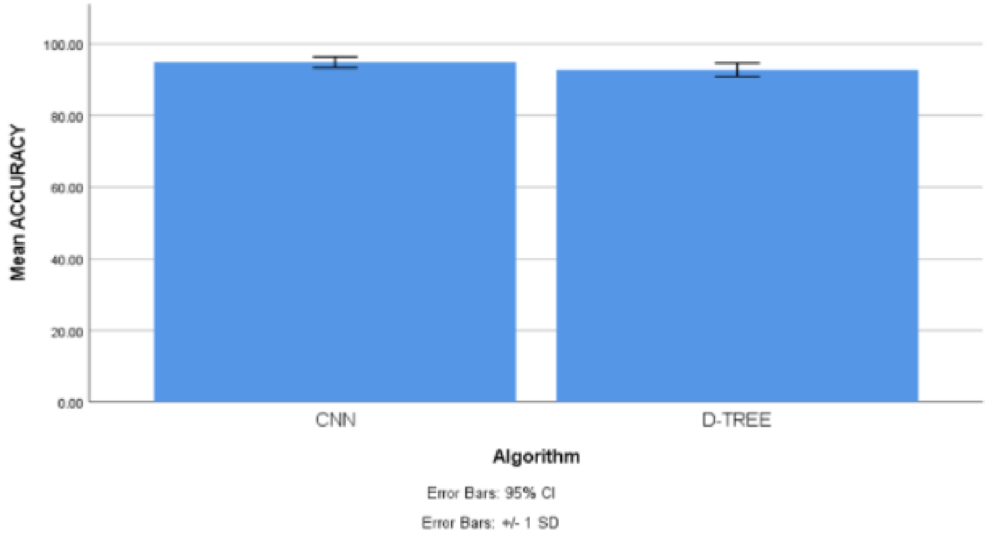

Fig. 1. Simple Bar graph for Decision Tree (D-Tree) Classifier accuracy rate is compared with Convolutional Neural Network (CNN) Classifier. The Decision Tree (D-Tree) Classifier is higher in terms of accuracy rate 94.15 when compared with Convolutional Neural Network (CNN) Classifier 96.32. Variable results with its standard deviation ranging from 80 lower to 90 higher Decision Tree (D-Tree) Classifier where Convolutional Neural Network (CNN) Classifier standard deviation ranging from 90 lower to 100 higher. There is a significant difference between Decision Tree (D-Tree) Classifier and Convolutional Neural Network (CNN) Classifier ($p<0.05$ Independent sample test). X-axis: Convolutional Neural Network (CNN) Classifier accuracy rate vs Decision Tree (D-Tree) Classifier Y-axis: Median of accuracy rate, for identification of keywords ± 1 SD with 95 % CI.