Convolutional Neural Network Prediction of House or Flat Rent in Metro Cities Compared to Decision Tree with Improved Accuracy

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ABSTRACT

Aim:The main aim of this research article is to improve the accuracy rate in prediction of house or flat rent in metro cities by using Convolutional Neural Network (CNN) in comparison with Naïve Bayes (NB) Classifier. Materials & Methods: The data set in this paper utilizes the publicly available Kaggle data set for prediction of house or flat rent in metro cities. The sample size of 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 0.8 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 Naïve Bayes (NB) where number of samples (N=10). Results: The Convolutional Neural Network (CNN) classifier has 95.46 higher accuracy rates when compared to the accuracy rate of Naïve Bayes (NB) is 89.0. The study has a significance value of $p<0.05$ i.e. $p=0.0332$. Conclusion: Convolutional Neural Network (CNN) provides the better outcomes in accuracy rate when compared to Naïve Bayes (NB) for prediction of house or flat rent in metro cities.

Keywords: Machine Learning, Rent, Metro Cities, Novel Convolutional Neural Network, Naive Bayes,Deep Learning.

INTRODUCTION

Presently, house lease forecast is a significant test found in metro urban areas(Hilber* 2017). The demand for the housing market continues to grow each year because of an expansion in populace and moving to different urban communities for their monetary reason(Wang et al. 2021). Forecasting the price of renting a temporary home is essential for people who will live long but not lastingly and individuals who would rather not face any challenge during the house development. In this study, a novel convolutional neural network (CNN) algorithm(Chiu, Chen, and Lee 2021) is used for the prediction of house rent in urban areas. It provides a summary of forecasting markets and, together, the current business sectors that form it simpler to anticipate the market. Estimating rental housing plays an important role in many areas of application such as land business, financial aspects, banking areas and furthermore purchaser and venders(Mohd et al. 2020).

Numerous researchers have presented their work on house rent forecast frameworks utilizing artificial intelligence calculations throughout recent years(Phan 2018; Shahi et al., n.d.). IEEE Explore distributed 83 examination papers, and Google Scholar tracked down 128 articles. Singh et al.(Singh, Sharma, and Dubey 2020) utilized the idea of huge information to foresee lodging deal information in Iowa, utilizing three models to figure house deal costs: regression, random forest and Naive Bayes models. Park and Bae(Park and Bae 2015) tended to the house cost expectation issue considering the lodging information accessible for Virginia County. To tackle the issue, the researchers have utilized artificial intelligence procedures like Naive Bayesian, AdaBoost, and RIPPER to forecast a house cost grouping model. Limsombunchai et al.(Limsombunchai 2004) utilized machine learning strategy (Artificial Neural Network) to anticipate the benefit of possessing a house in New Zealand and observed that machine learning technique was better in the expectation. Also, Do and Grudnitski(Do and Grudnitski 1992) applied the OLS and Artificial Neural Network way to deal with anticipate the selling cost of single-family homes in San Diego, California, the United States of America. Their outcomes showed that the machine learning strategy outflanked the OLS relapses in anticipating the housing values. Muhammad Fahmi Mukhlishin et.al,(Mukhlishin, Saputra, and Wibowo 2017) utilizes a few strategies to anticipate the worth of land and house. This paper analyzes Artificial Neural Network, and K-Nearest Neighbor to track down the most proper technique to decide the vender's cost. Banerjee D et.al,(Banerjee and Dutta 2017) acquainted with predicting the Housing esteem forecast using machine learning Techniques. The performance of the proposed method is estimated by the four boundaries of accuracy, precision, specificity, and sensitivity. The most refered to article was(Varma, Sarma, and Doshi 2018), in Google researcher investigate with 45 references and 2843 full text sees.(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 significant weakness with the Naïve Bayes (NB) technique is that it is shaky, implying that a little change in the information can prompt an enormous change in the construction. They are frequently moderately erroneous and take a long preparation time on huge datasets. To defeat this issue, this paper proposes a novel convolutional brain organization (CNN) calculation in examination with innocent bayes (NB) calculation. The outcome was estimated utilizing Precision, Recall and Accuracy for assessing the viability of the proposed strategy.

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. In this review, the dataset is gathered from nobroker.com. This dataset comprises of 90 house highlights and 1302 houses with lease costs. The database is divided by the amount of 75% training and 25% testing. Two sets are taken and 10 samples for each sets, absolute samples considered are 20. Set 1 was a Naive Bayes (NB) calculation and Set 2 was a novel Convolutional Neural Network (CNN) calculation. The result is acquired by involving Python programming for the forecast of house lease costs. The estimation is performed using G-power 0.8 with alpha and beta characteristics 0.05, 0.2 with a certainty stretch at 95%.

Naive Bayes (NB) Algorithm

The sample group 1 is the Naive Bayes (NB) algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems. The steps involved in the implementation of the faster NB algorithm are described as follows.Naive Bayes (NB) is a statistical classification technique used to solve problems concerning classification. It is a fast, precise, reliable algorithm and has high accuracy and speed on large datasets. Naive Bayes implies that the existence of a specific characteristic is independent of other characteristics being present. For instance, if the fruit is orange in color, ten centimeters in diameter and round in shape, the fruit could be viewed as orange. Every one of these properties, both separately and autonomously, lead to the likelihood that the fruit is orange while paying little regard to whether they rely upon one another, and that is the reason it is called ' Naive.' Bayes Theorem: The theorem obtains the likelihood of an event taking place provided that another event has already taken place.

Pseudocode of Naive Bayes (NB) Algorithm

1. In the training stage, training data consisting of both input and target output is given to the Naive Bayes classifier.

2. The prior probabilities of the target output classes are calculated from the training data.

3. The likelihood probabilities of input features i.e. probability of input features given that probability of target output is known is calculated.

4. In the testing stage, testing data consisting of new inputs is given to the classifier.

5. The posterior probability i.e. probability of output classes given that probability of input features is known is calculated. Its formula is given as

It's expressed by the following formula

P(L|M) – the likelihood of event L occurring, given event M has occurred

P(M|L) – the likelihood of event M occurring, given event L has occurred

P(L) – the likelihood of event L

P(M) – the likelihood of event M

events L and M are independent of one another.

For classification, the Nave Bayesian finds the probability for the unknown in any given class and selects the class with the highest probability. The general and standardized real estate characteristics are often listed separately from the asking price and general description because these characteristics are separately listed in a structured way, they can be easily compared across the whole range of potential houses because every house also has its own unique characteristics, such as a particular view or type of sink, house sellers can provide a summary of all the important features of the house in the description.

Novel Convolutional neural network

The sample preparation group 2 is the novel convolutional neural network (CNN), which is network architecture for deep learning which learns directly from data, eliminating the need for manual feature extraction. The experimental results show that the proposed CNN method has achieved better accuracy results.

Convolutional neural network is a type of deep neural network, which have neurons, arranged in three dimensions namely width, height and depth(LeCun, Kavukcuoglu, and Farabet 2010). It comprises three main layers, input layer, hidden layer and output layer. A CNN can have tens to hundreds of hidden layers depending on the classification task and the amount of data. The hidden layer consists of a convolutional layer, rectified linear unit (ReLU) layer, pooling layer and fully connected layer. All these layers are stacked together to build a full Convonet. The CNN predicts the housing price through a series of transformations and analyses to the input layer. First, it transforms the input layer into a 4×4 matrix that serves as the data source for the first layer of the convolutional layer. The input of the first convolutional layer is set to: length 2, width 2, height 1 and the output thickness of 32. A 2 × 2 × 32 matrix is output by the convolutional matrix operation and the moving step is set to 1 in the first convolution operation. The matrix data obtained after the operation in the first convolutional layer is used as the data source of the second convolutional layer. Similarly, the input of the second convolutional layer is set to a height of 32, the output thickness of 64, and a moving step length of 1, and then a 4 × 4 × 64 matrix data is output after the convolutional matrix operation. CNN can well combine the processing and storage of the second-hand house information, and it can adaptively learn the sample data intelligently with the use of the relevant feature data and mathematical algorithm. In addition, CNN can deeply grasp the features of objects, so it is very suitable to solve the existing problems.

Pseudocode for Novel Convolutional neural network

```
Classify (X,Y,x) || x:training data , y: class labels of X, x:unknown sample
FOR i = 1 to m do
Compute distance d(X,x)
END FOR
Compute set I containing indices for the CNN - smallest distance d(xi,x)
Return majority label for{Y;where i ∈ 1}
```

The calculations run with least necessities of equipment are Intel i5, 50-gigabyte hard plate limit, and 4 gigabytes of Random Access Memory and the Software is required to run the algorithm on any windows operating system with python Anaconda Spyder with version 4.1.5.

Statistical Analysis

The output is obtained by using Python software(Milano 2013). 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(Pallant 2010). 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 (96.00%), mean value (95%) and standard deviation value (0.23942). Dependent variables are accuracy and independent variables are image size.

RESULTS

Figure 1 shows the simple bar graph for Naïve Bayes (NB) Classifier accuracy rate is compared with Convolutional Neural Network (CNN) Classifier. The Convolutional Neural Network (CNN) Classifier is higher in terms of accuracy rate 96.00 when compared with Naïve Bayes (NB) Classifier 93.00. Variable results with its standard deviation ranging from 80 lower to 90 higher Naïve Bayes (NB) Classifier where Convolutional Neural Network (CNN) Classifier standard deviation ranging from 90 lower to 100 higher. There is a significant difference between Naïve Bayes (NB) Classifier and Convolutional Neural Network (CNN) Classifier ($p<0.05$ Independent sample test). X-axis: Convolutional Neural Network (CNN) Classifier accuracy rate vs Naïve Bayes (NB) 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 Naïve Bayes (NB) and novel Convolutional Neural Network (CNN) Classifier. The accuracy rate of Naïve Bayes (NB) is 93.00 and Convolutional Neural Network (CNN) has 96.00. In all aspects of parameters Convolutional Neural Network (CNN) provides better performance compared with the Naïve Bayes (NB) of Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate.

Table. 2 shows the statistical calculation such as Median, standard deviation and standard error Median for Naïve Bayes (NB) and Convolutional Neural Network (CNN). The accuracy rate parameter used in the t-test. The mean accuracy rate of Naïve Bayes (NB) is 93.00 and Convolutional Neural Network (CNN) is 96.00. The Standard Deviation of Naïve Bayes (NB) is 1.02343 and Convolutional Neural Network (CNN) is 0.20000. The Standard Error Median of Naïve Bayes (NB) is 0.82738 and Convolutional Neural Network (CNN) is 0.17283.

Table. 3 displays the statistical calculations for independent samples tested between Naïve Bayes (NB) and Convolutional Neural Network (CNN). The statistical calculations for independent samples test between Naïve Bayes (NB) and Convolutional Neural Network (CNN). There exists a statistically significant difference between the two groups ($p=0.0332$; $p<0.05$) with confidence interval 95%. This independent sample test consists of between Naïve Bayes (NB) and Convolutional Neural Network (CNN) significance as 0.0332, significance 2-tailed(.000), Mean difference(12.983,12.402), standard error difference(0.8876,0.6782), and lower(11.9284,10.6792) and upper (13.7834,12.7732) interval difference.

DISCUSSION

In this paper, a novel house rent forecasting model based on convolutional neural network (CNN) and naïve bayes (NB) is presented. Compared to the naïve bayes (NB) algorithm, CNN is powerful and easy to implement. The housing price sample data of Chongqing are adopted to study the forecasting performance of CNN model compared with NB method. The experimental results show that CNN has higher forecasting accuracy than the NB algorithm. In the experimental process, 80% of the data are randomly selected as the training set and 20% of the data as the testing set for each iteration. The whole process is repeated ten times and the average value is taken as the final result. The loss function of the CNN converges and the final error arrives at a relatively lower point eventually(Srirutchataboon et al. 2021). The python software is used to build the CNN model in the experimental process. The model includes two convolutional layers and the Relu function is adopted as the activation function, meanwhile the dropout method is also engaged to avoid over-fitting. Finally, by adjusting the loss function, the whole Novel Rent Prediction process is fully constructed. The confusion matrix is a matrix that maps the predicted outputs across actual outputs. It is often used to describe the performance of a classification model on a set of test data. Important metrics were computed from the confusion matrix in order to evaluate the classification models. In addition to correct classification rate or accuracy other metrics that were computed for evaluation were True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Sensitivity, Specificity and Accuracy.There exists a statistically significant difference between the two groups ($p=0.0332$; $p<0.05$) with confidence interval 95%.

Many house rent Novel Rent Prediction systems have been developed over the past decades. P. Durganjali, et al.(Durganjali and Pujitha 2019), proposed a house resale price Novel Rent Prediction using classification algorithms. In this paper, the resale price Novel Rent Prediction of the house is done using different classification algorithms like Logistic regression, Decision tree, Naive Bayes and Random forest is used and we use AdaBoost algorithm for boosting up the weak learners to strong learners. Lee and Park(C. Lee and Park 2020), who used the Bayesian neural network as a tool to measure the uncertainty in property valuation, and Liu et al.(Liu et al. 2020), who predicted the property price using a pre-trained CNN model based on neighboring data samples. It has shown accuracy of about 92.38%. H Lee(H. Lee et al. 2020) proposed the Novel Rent Prediction and factors of apartment prices in Seoul using a convolutional neural networks (CNN) model that has shown excellent performance as a predictive model of image data and provides an accuracy rate of 94.7%. Y Chen(Chen, Xue, and Zhang 2021) proposed an effective model of house price Novel Rent Prediction based on machine learning and deep learning methods and achieved an accuracy rate of 96%

The limitation of the proposed CNN method is a multi-stage model, where each stage is an independent component. Thus, it cannot be trained end-to-end. The convolutional neural network algorithm helps to fulfill customers by increasing the accuracy of estate choice and reducing the risk of investing in an estate. A lot of features that could be added to make the system more widely acceptable. One of the major future scopes is adding an estate database of more cities which will provide the user to explore more estates and reach an accurate decision. More factors like recession that affect the house prices shall be added. In-depth details of every property will be added to provide ample details of a desired estate. This will help the system to run on a larger level.

CONCLUSION

The proposed model exhibits the Naïve Bayes (NB) 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 96.00 is higher compared with Naïve Bayes (NB) that has an accuracy rate of 93.00 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 Naïve Bayes (NB) and Convolutional Neural Network (CNN) Classifier for predicting the Novel Rent Prediction of house or flat rent in metro cities with improved accuracy rate. The accuracy rate of Naïve Bayes (NB) is 93.00 and Convolutional Neural Network (CNN) has 96.00.

SI.No.	Test Size	Convolutional Neural Network (CNN) Classifier	Naïve Bayes (NB) Classifier
1	530	93.12	87.11
2	560	93.17	87.19
3	590	93.23	87.31
4	620	93.29	87.53
5	650	94.05	87.85
6	680	94.12	88. 32
7	710	94.39	88.68
8	740	95.09	88.78
9	770	95.12	88.88
10	800	96.00	93.00

Table. 2. The statistical calculation such as Median, standard deviation and standard error Median for Naïve Bayes (NB) and Convolutional Neural Network (CNN). The accuracy rate parameter used in the t-test. The mean accuracy rate of Naïve Bayes (NB) is 93.00 and Convolutional Neural Network (CNN) is 96.00. The Standard Deviation of Naïve Bayes (NB) is 1.02343 and Convolutional Neural Network (CNN) is 0.20000. The Standard Error Median of Naïve Bayes (NB) is 0.82738 and Convolutional Neural Network (CNN) is 0.17283.

Group		N	Mean	Standard Deviation	Standard Error Mean
ACCURACY	CONVOLUTIONAL NEURAL NETWORK (CNN)	10	96.00	0.20000	0.17283

	NAIVE BAYES (NB)	10	93.00	1.02343	0.82738

Table 3. The statistical calculations for independent samples test between Naïve Bayes (NB) and Convolutional Neural Network (CNN). There exists a statistically significant difference between the two groups (p=0.0332; p<0.05) with confidence interval 95%. This independent sample test consists of between Naïve Bayes (NB) and Convolutional Neural Network (CNN) significance as 0.0332, significance 2-tailed(.000), Mean difference(12.983,12.402), standard error difference(0.8876,0.6782), and lower(11.9284,10.6792) and upper (13.7834,12.7732) 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**	9.234	0.0332	16.571	18	.000	12.983	0.8876	11.9284	13.7834
	Equal variances not assumed			9.2918	12.672	.000	12.402	0.6782	10.6792	12.7732

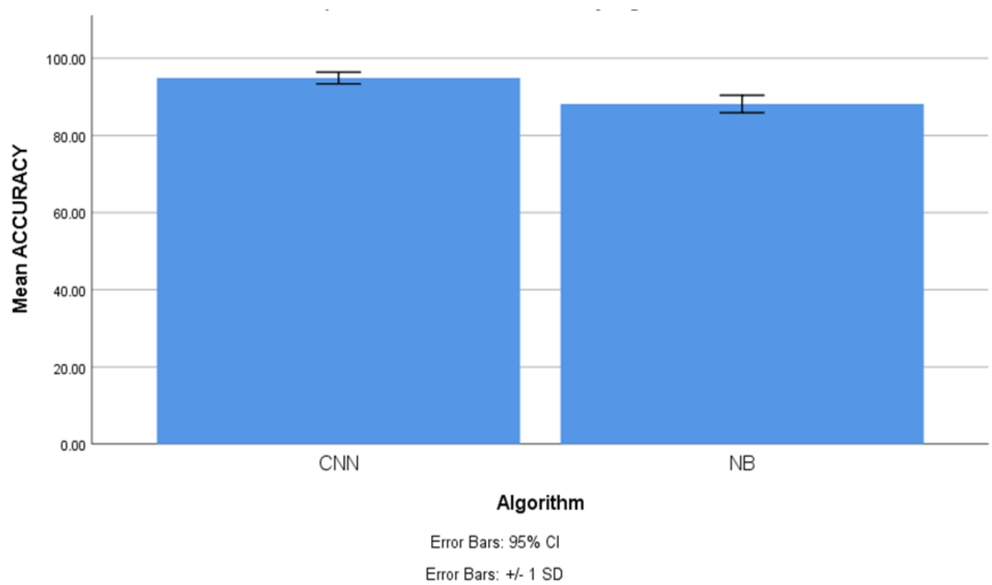

Fig. 1. Simple Bar graph for Naïve Bayes (NB) Classifier accuracy rate is compared with Convolutional Neural Network (CNN) Classifier. The Naïve Bayes (NB) Classifier is higher in terms of accuracy rate 93.00 when compared with Convolutional Neural Network (CNN) Classifier 96.00. Variable results with its standard deviation ranging from 80 lower to 90 higher Naïve Bayes (NB) Classifier where Convolutional Neural Network (CNN) Classifier standard deviation ranging from 90 lower to 100 higher. There is a significant difference between Naïve Bayes (NB) Classifier and Convolutional Neural Network (CNN) Classifier ($p<0.05$ Independent sample test). X-axis: Convolutional Neural Network (CNN) Classifier accuracy rate vs Naïve Bayes (NB) Classifier Y-axis: Median of accuracy rate, for identification of keywords ± 1 SD with 95 % CI.