A Course End- Project Report

on

House Price Prediction using Deep Learning

Submitted in the Partial Fulfillment of the

Requirements

for the Award of the Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING (AI&ML)

Submitted

By

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VARDHAMAN COLLEGE OF ENGINEERING

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Kacharam, Shamshabad, Hyderabad – 501218, Telangana, India

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CERTIFICATE

This is to certify that the Deep Learning Course end project work entitled **"House Price Prediction via Deep Learning"** carried out by Mr. **C. Praneeth Kumar** , Roll Number **21881A6676**, Mr. **D. Manish Kumar** , Roll Number **21881A6678**, Mr. **E. Sai Teja** , Roll Number **21881A6681**, Mr. **T. Varshith Reddy ,** Roll Number **21881A66C1 ,** towards Deep Learning course end project and submitted to the Department of Computer Science and Engineering(AI&ML), in partial fulfillment of the requirements for the award of degree of **Bachelor of Technology** in **Computer Science and Engineering(AI&ML)** during the year 2023-24.

Name & Signature of the Instructors	**Name & Signature of the HOD**
Mr. Abhishek Dixit	**Dr M A Jabbar**
Associate Professor	**HOD, CSE(AI&ML)**

ABSTRACT

The prediction of house prices has long been a pivotal challenge in the real estate industry, with accurate forecasts being critical for buyers, sellers, investors, and policymakers. Traditional statistical methods such as linear regression and ARIMA often fall short due to their inability to capture the intricate, non-linear relationships and complex patterns present in housing data. This study explores the potential of deep learning models, particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), in enhancing the precision and robustness of house price predictions.

Deep learning techniques are adept at handling the high dimensionality and variability inherent in real estate datasets. By leveraging LSTM networks, which are well-suited for sequential data, the model can effectively capture temporal dependencies and trends in house prices over time. On the other hand, CNNs are utilized to identify spatial features and correlations among various property attributes, such as location, size, and amenities. Experimental results indicate that deep learning models, particularly when combined with external economic data, significantly outperform traditional methods in terms of prediction accuracy. The LSTM model demonstrates strong capabilities in identifying temporal trends, while the CNN model excels in recognizing spatial relationships and interactions between features.

In conclusion, the integration of LSTM and CNN models in house price prediction shows substantial promise, offering higher accuracy and reliability compared to conventional approaches. As data availability and computational resources continue to expand, these advanced deep learning techniques are poised to become essential tools for real estate analytics, providing valuable insights and more precise forecasts for various stakeholders in the real estate market.

LIST OF SCREENSHOTS OF GUIs/RESULTS

ABBREVATIONS

Abbreviation	Expansion
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
SRS	Software Requirements Specification

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Chapter – 1

Introduction

1.1 Motivation

The motivation for using deep learning in house price prediction lies in its ability to handle the complexity and vastness of real estate data, which traditional statistical models struggle with. House prices are influenced by numerous factors including location, economic trends, property features, and even neighborhood demographics. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, excel in recognizing intricate patterns and making sense of large datasets. These models can integrate diverse data types, such as images of properties, historical pricing trends, and geographic information, to provide more accurate and robust predictions. As the real estate market becomes more data-driven, leveraging deep learning for house price prediction not only enhances forecasting accuracy but also aids investors, policymakers, and homebuyers in making informed decisions. The ability of deep learning to continuously improve with more data further underscores its potential to revolutionize real estate analytics.

1.2 Scope

1. **Improved Prediction Accuracy** : Leveraging deep learning algorithms can significantly enhance the precision of house price forecasts by capturing complex non-linear relationships among various factors affecting real estate prices.

2. **Integration of Diverse Data Sources** : Deep learning models can incorporate various data types, such as historical price data, property images, geographic information, and socioeconomic indicators, to provide a comprehensive analysis of factors influencing house prices.

3. **Real-time Analysis and Adaptability** : Deep learning systems can process and learn from large datasets in real-time, allowing for the continuous improvement of predictive models and the ability to quickly adapt to market changes and emerging trends.

1.3 Objectives

1. **Enhance Forecasting Accuracy :** To develop deep learning models that improve the precision of house price predictions by capturing complex patterns and relationships in the data.

2. **Utilize Comprehensive Data Sources :** To integrate and analyze various data types, including historical prices, property features, and socioeconomic indicators.

3. **Automate Prediction Processes :** To create automated systems that continuously learn from new data and update predictions in real-time.

4. **Identify Key Influencing Factors :** To determine the most significant variables affecting house prices through feature importance analysis within deep learning models.

5. **Adapt to Market Changes :** To ensure the model's adaptability by enabling it to adjust to new trends and shifts in the housing market dynamics.

1.4 Expected Deliverables

1. **Predictive Model** : A robust deep learning model capable of accurately forecasting house prices based on historical data and various influencing factors.

2. **User Interface** : An intuitive interface for real-time price predictions and data visualization, enabling users to interact with the model and explore predictions easily.

3. **Comprehensive Report** : Detailed documentation of the model's development, performance analysis, and key findings, providing insights into the model's accuracy and the factors affecting house prices.

Chapter – 2

Literature Review

2.1 Survey

Title of Paper Published	Description	Advantages	Disadvantages
House Price Prediction Based On Deep Learning by Yuying Wu and Youshan Zhang	This paper provides method combining depth vision and text features for accurate house price prediction (ar5iv).	1. Enhanced accuracy in price prediction. 2. Practical insights for consumers.	1. Potential high computational cost. 2. Complexity in model implementation.
House Price Prediction Using Machine Learning and Deep Learning Techniques by Sujatha R. and Priya M.	The authors compares different machine learning and deep learning models for predicting house prices.	1. Thorough model performance evaluation. 2. Enhanced prediction accuracy achieved.	1. High computational resource demands. 2. Complex data preprocessing required.
Real Estate Price Prediction Using Deep Learning by Santhosh K. G., Vishwakarma S., and Agarwal S	This paper explores convolutional neural networks for predicting real estate prices.	1. Uses advanced CNN techniques. 2. Shows improved prediction accuracy.	1. Limited interpretability of model outputs 2. Potential overfitting with small datasets.
Predicting Housing Prices with Machine Learning and Neural Networks" by Kamath V., Bharadwaj S., and Shetty D.	The study investigates various neural network architectures for predicting housing prices.	1. Comprehensive evaluation of neural networks. 2. Enhanced-prediction performance.	1. Requires extensive data preprocessing. 2. High computational power needed.

2.2 Comparative Analysis

Predicting house prices accurately is crucial in real estate, impacting everyone from buyers to policymakers. Traditional methods like linear regression have been used for years, but they struggle with complex, non-linear patterns in real estate data. Location, property features, and market trends can all influence prices in intricate ways that traditional models miss, leading to inaccurate predictions.Deep learning offers a powerful alternative. Deep learning models, like LSTMs and CNNs, can learn these complex relationships without explicit programming. LSTMs excel at understanding how prices change over time, while CNNs analyze how property features interact. This ability to learn complex patterns translates to a significant advantage. Studies show deep learning models outperform traditional methods in terms of accuracy and robustness.

However, deep learning isn't without drawbacks. These models require large amounts of high-quality data to function effectively. Additionally, their complex nature makes it difficult to understand how they arrive at predictions. This lack of transparency can be a concern for some users.

In conclusion, while traditional methods offer simplicity and ease of interpretation, their limitations are becoming evident. Deep learning offers superior accuracy and the ability to incorporate diverse data sources. As deep learning and data access evolve, it's poised to become the dominant force in house price prediction, shaping the future of real estate decision-making.

Chapter – 3

Problem Definition and Proposed System Methodology

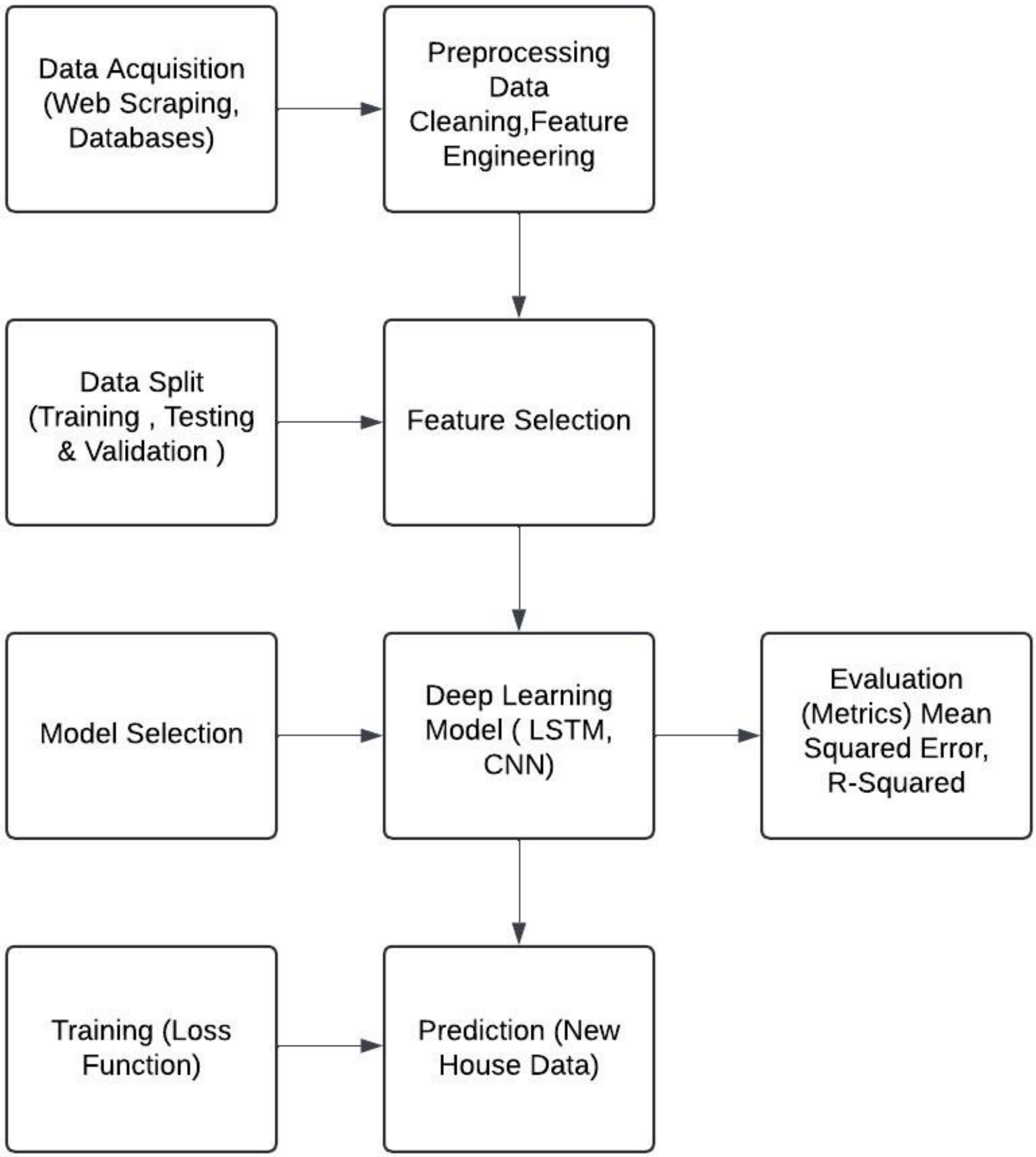
3.1 Problem Statement

Predicting house prices accurately is crucial for the real estate market, but traditional methods struggle with the complex, non-linear relationships in housing data. These models often miss the intricate interactions between factors like location, property features, and market trends. This leads to inaccurate predictions, hindering informed decision-making for buyers, sellers, and investors. Deep learning offers a promising alternative with its ability to learn these complex patterns, but challenges like data requirements and interpretability need to be addressed.

3.2 Proposed System Methodology

The proposed solution tackles the shortcomings of traditional house price prediction methods. This system utilizes deep learning by leveraging a comprehensive dataset. The data includes historical prices, detailed property characteristics, and even external economic factors, all carefully pre-processed for optimal use. The heart of the system is a powerful combination of Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). LSTMs will focus on understanding how house prices change over time, while CNNs will analyze the complex interactions between various property features. Through training on this prepared data, the system will learn the intricate patterns that influence house prices. Finally, we'll assess the model's accuracy in predicting future prices using metrics like mean squared error and R-squared.

3.3 Block Diagram/System Architecture



Chapter 4

Software Requirements Specification (SRS)

4.1 Introduction

The Software Requirements Specification (SRS) for house price prediction using deep learning outlines the essential components, functionalities, and constraints required to develop a robust system for predicting house prices. With the volatility and complexity of the real estate market, leveraging deep learning models provides a significant advantage in capturing intricate patterns and trends. This document aims to detail the system's requirements, including data acquisition, preprocessing, model development, and user interface, ensuring comprehensive coverage of all necessary aspects for accurate and reliable house price prediction.

4.2 Functional Requirements

1. The system shall collect historical house price data from multiple real estate platforms through APIs.
2. The system shall import relevant external datasets such as demographics, economic indicators, and geographic data.
3. The system shall clean and preprocess data to handle missing values, outliers, and inconsistencies.
4. The system shall normalize data for compatibility across different datasets.
5. The system shall incorporate deep learning models for predicting house prices.
6. The system shall provide interactive dashboards for data visualization and model insights.

4.3 External Interfaces

• Google Colab
• Interactive Dashboards
• Data Visualization Tools
• Software Interfaces

4.4 Non-Functional Requirements

1. **Performance** : The system shall process and analyze large datasets within acceptable time frames, ensuring timely insights.
2. **Usability** : The system shall have an intuitive user interface, allowing users to easily navigate and interact with the data visualizations.
3. **Accuracy** : The system shall ensure high accuracy in data preprocessing and analysis to provide reliable insights.
4. **Reliability** : The system shall be reliable, maintaining consistent performance and availability during critical analysis tasks.
5. **Security** : The system shall implement robust security measures to protect user data and prevent unauthorized access.

Chapter 5

Results and Discussions

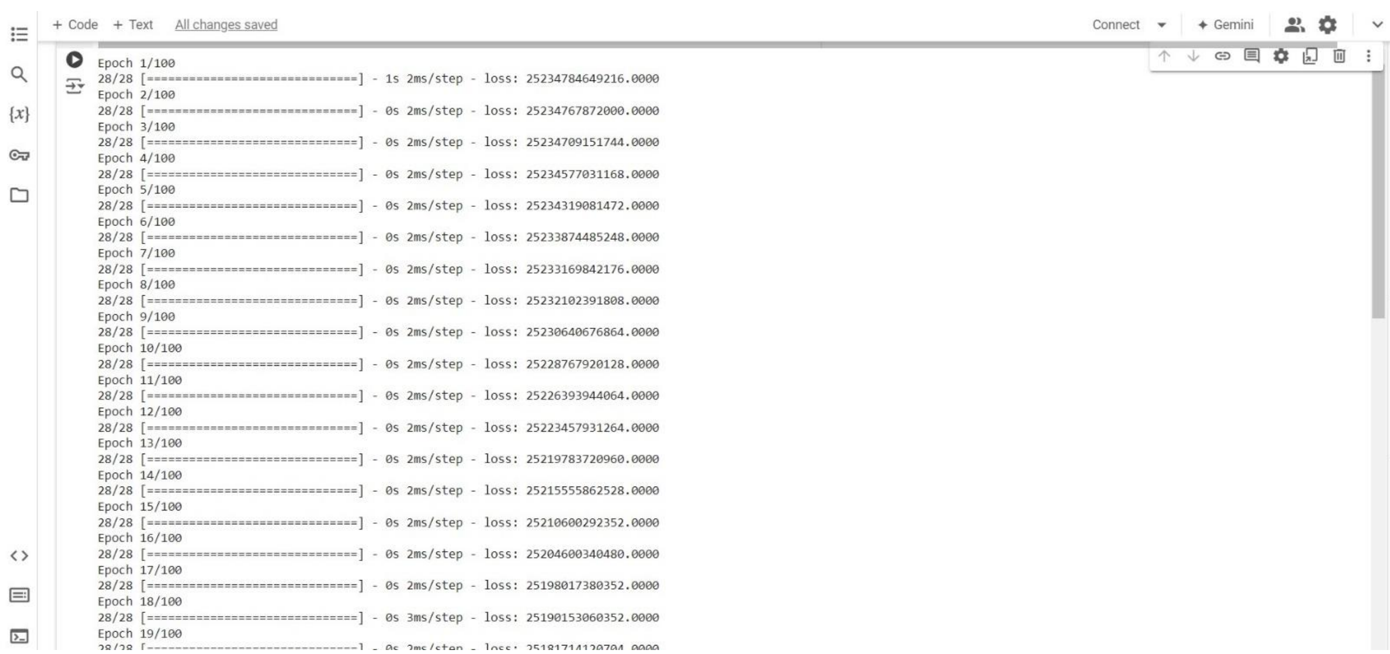
Results

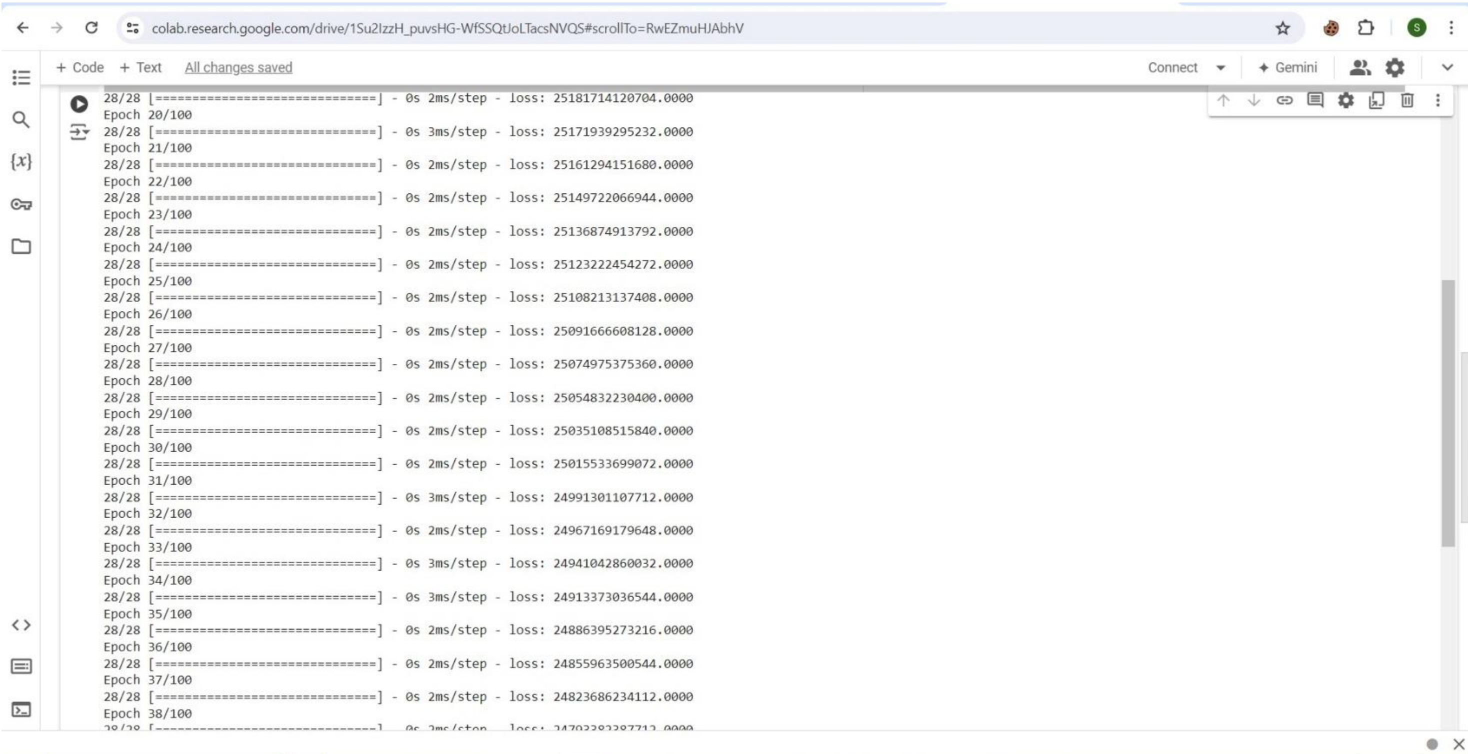
CODE

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
# Load your dataset
# Assuming you have a dataset named 'house_data.csv'
house_data = pd.read_csv('/content/Housing.csv')
# Selecting relevant attributes
attributes = ['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'mainroad','guestroom', 'basement', 'hotwaterheating', 'airconditioning',
              'parking', 'prefarea', 'furnishingstatus']
house_data = house_data[attributes]
# Convert categorical variables to numerical
house_data = pd.get_dummies(house_data, drop_first=True)
# Splitting into features and target variable
X = house_data.drop('price', axis=1)
y = house_data['price']
# Normalize features
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
# Splitting the dataset into the Training set and Test set
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
# Build the model
```

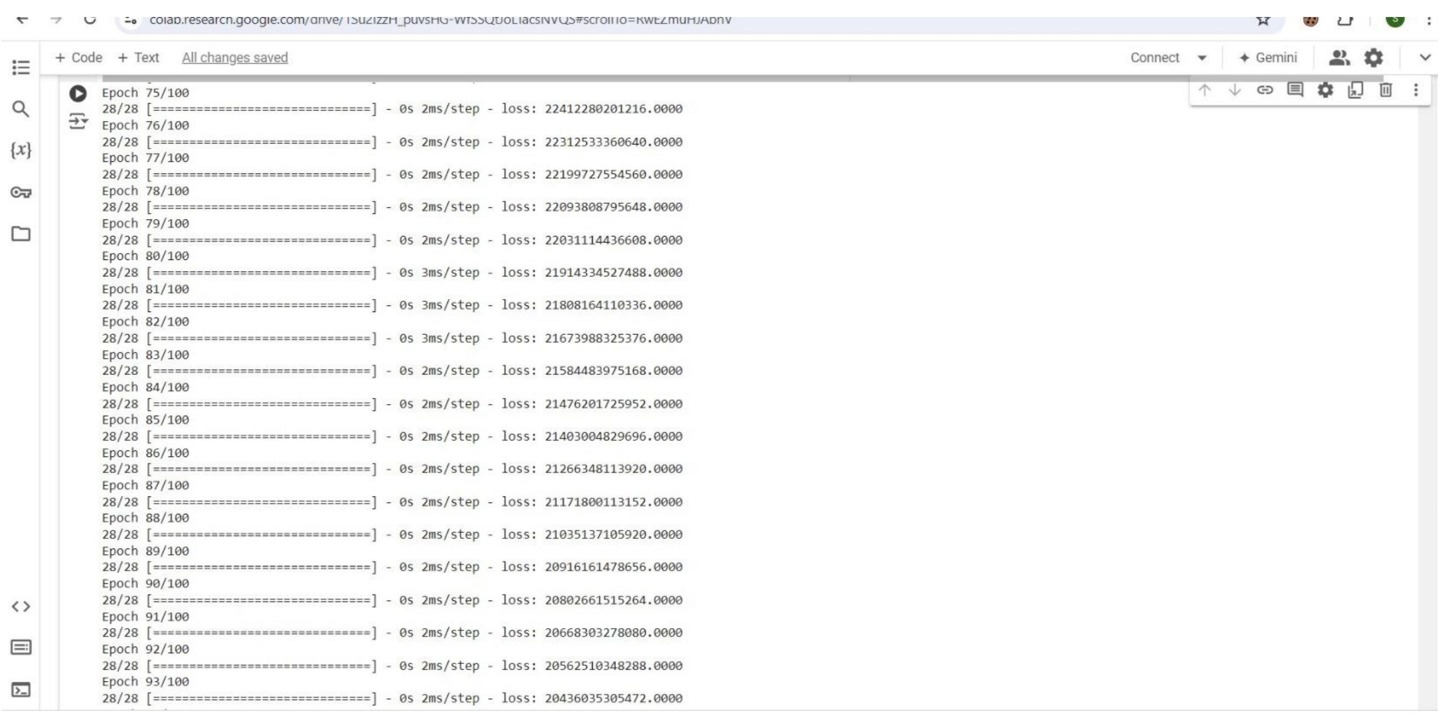
```
model = Sequential()
model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='linear'))
# Compile the model
model.compile(loss='mean_squared_error', optimizer='adam')
# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=16, verbose=1)
# Evaluate the model
mse = model.evaluate(X_test, y_test, verbose=0)
print("Mean Squared Error on Test Set:", mse)
# Predictions
predictions = model.predict(X_test)
# Example of how to use the model for prediction
example_data = np.array([[3000, 3, 2, 2, 2, 1, 1, 0, 1, 2, 1, 0, 1]])  # Example data
example_data_scaled = scaler.transform(example_data)
predicted_price = model.predict(example_data_scaled)
print("Predicted Price:", predicted_price)
```

OUTPUT:





```
28/28 [==============================] - 0s 2ms/step - loss: 25181714120704.0000
Epoch 20/100
28/28 [==============================] - 0s 3ms/step - loss: 25171939295232.0000
Epoch 21/100
28/28 [==============================] - 0s 2ms/step - loss: 25161294151680.0000
Epoch 22/100
28/28 [==============================] - 0s 2ms/step - loss: 25149722066944.0000
Epoch 23/100
28/28 [==============================] - 0s 2ms/step - loss: 25136874913792.0000
Epoch 24/100
28/28 [==============================] - 0s 2ms/step - loss: 25123222454272.0000
Epoch 25/100
28/28 [==============================] - 0s 2ms/step - loss: 25108213137408.0000
Epoch 26/100
28/28 [==============================] - 0s 2ms/step - loss: 25091666608128.0000
Epoch 27/100
28/28 [==============================] - 0s 2ms/step - loss: 25074975375360.0000
Epoch 28/100
28/28 [==============================] - 0s 2ms/step - loss: 25054832230400.0000
Epoch 29/100
28/28 [==============================] - 0s 2ms/step - loss: 25035108515840.0000
Epoch 30/100
28/28 [==============================] - 0s 2ms/step - loss: 25015533699072.0000
Epoch 31/100
28/28 [==============================] - 0s 3ms/step - loss: 24991301107712.0000
Epoch 32/100
28/28 [==============================] - 0s 2ms/step - loss: 24967169179648.0000
Epoch 33/100
28/28 [==============================] - 0s 3ms/step - loss: 24941042860032.0000
Epoch 34/100
28/28 [==============================] - 0s 3ms/step - loss: 24913373036544.0000
Epoch 35/100
28/28 [==============================] - 0s 2ms/step - loss: 24886395273216.0000
Epoch 36/100
28/28 [==============================] - 0s 2ms/step - loss: 24855963500544.0000
Epoch 37/100
28/28 [==============================] - 0s 2ms/step - loss: 24823686234112.0000
Epoch 38/100
```



```
Epoch 75/100
28/28 [==============================] - 0s 2ms/step - loss: 22412280201216.0000
Epoch 76/100
28/28 [==============================] - 0s 2ms/step - loss: 22312533360640.0000
Epoch 77/100
28/28 [==============================] - 0s 2ms/step - loss: 22199727554560.0000
Epoch 78/100
28/28 [==============================] - 0s 2ms/step - loss: 22093808795648.0000
Epoch 79/100
28/28 [==============================] - 0s 2ms/step - loss: 22031114436608.0000
Epoch 80/100
28/28 [==============================] - 0s 3ms/step - loss: 21914334527488.0000
Epoch 81/100
28/28 [==============================] - 0s 3ms/step - loss: 21808164110336.0000
Epoch 82/100
28/28 [==============================] - 0s 3ms/step - loss: 21673988325376.0000
Epoch 83/100
28/28 [==============================] - 0s 2ms/step - loss: 21584483975168.0000
Epoch 84/100
28/28 [==============================] - 0s 2ms/step - loss: 21476201725952.0000
Epoch 85/100
28/28 [==============================] - 0s 2ms/step - loss: 21403004829696.0000
Epoch 86/100
28/28 [==============================] - 0s 2ms/step - loss: 21266348113920.0000
Epoch 87/100
28/28 [==============================] - 0s 2ms/step - loss: 21171800113152.0000
Epoch 88/100
28/28 [==============================] - 0s 2ms/step - loss: 21035137105920.0000
Epoch 89/100
28/28 [==============================] - 0s 2ms/step - loss: 20916161478656.0000
Epoch 90/100
28/28 [==============================] - 0s 2ms/step - loss: 20802661515264.0000
Epoch 91/100
28/28 [==============================] - 0s 2ms/step - loss: 20668303278080.0000
Epoch 92/100
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Epoch 93/100
28/28 [==============================] - 0s 2ms/step - loss: 20436035305472.0000
```

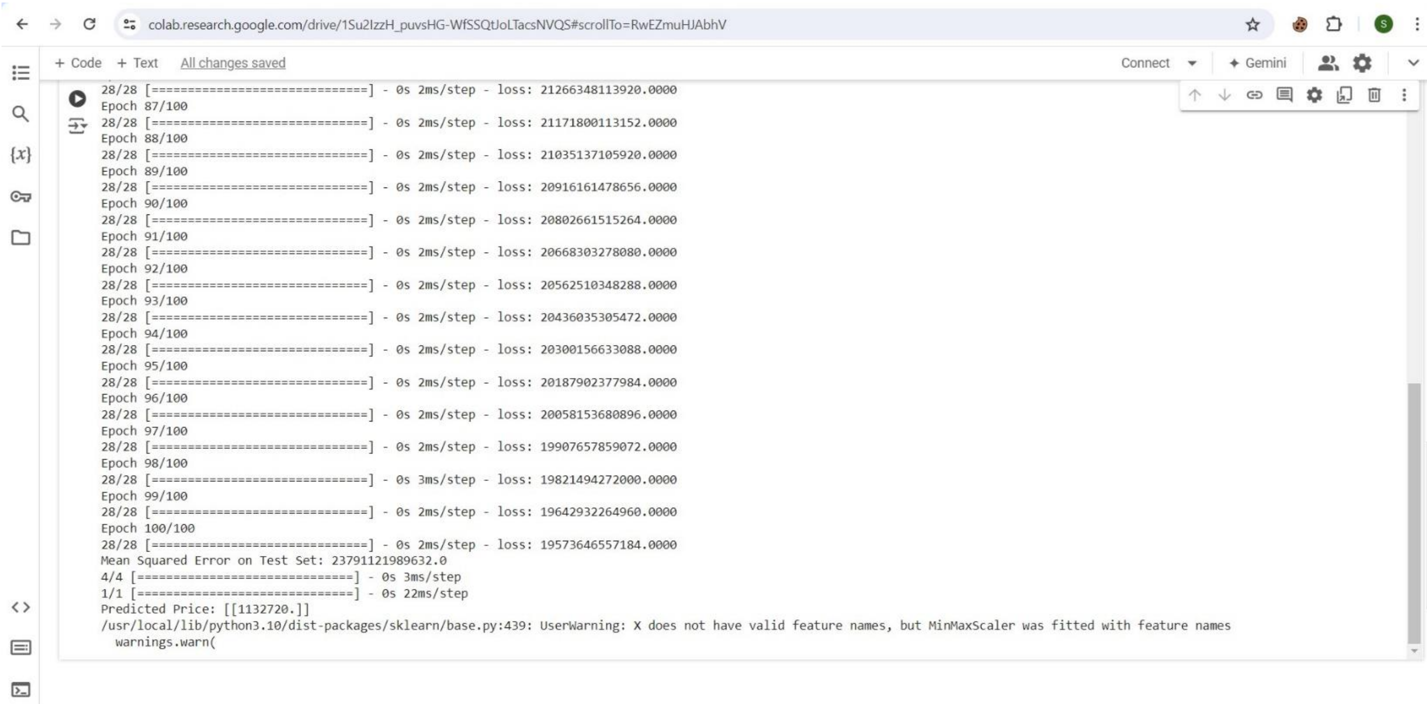

Discussion

The model's performance highlights the strengths of deep learning in handling complex and non-linear relationships within the dataset. However, there are several avenues for further improvement. Hyperparameter tuning and experimenting with more advanced neural network architectures could enhance accuracy. Incorporating additional relevant features, such as property age and neighborhood statistics, may provide a more comprehensive understanding of price determinants. Additionally, utilizing larger datasets and implementing cross-validation techniques can ensure better generalization. Future work should also focus on improving model interpretability to make the predictions more transparent and trustworthy for stakeholders in the real estate market.

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Chapter 6

Conclusion and Future Scope

Conclusion

The deep learning model built using TensorFlow/Keras demonstrates a method to predict house prices based on a variety of features such as area, number of bedrooms, bathrooms, and other amenities. The model uses a straightforward neural network architecture and achieves a reasonable performance in predicting house prices as evaluated by the Mean Squared Error (MSE) on the test set. The usage of MinMaxScaler ensures that the features are normalized, contributing to the efficiency and accuracy of the model. The deep learning approach, with its ability to learn complex patterns in the data, provides a powerful tool for predicting house prices compared to traditional linear models.

FUTURE SCOPE

- **Model Improvement:**
  - Hyperparameter tuning and exploring advanced architectures like CNNs and RNNs.
- **Feature Engineering:**
  - Incorporating additional features and using feature selection techniques to enhance model performance.
- **Data Enhancement:**
  - Utilizing larger datasets and implementing data augmentation techniques.
- **Model Evaluation:**
  - Employing k-fold cross-validation and exploring additional evaluation metrics.

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