Design And Development of Text-to-Code Generator System

A

MAJOR PROJECT-I REPORT

Submitted in partial fulfillment of the requirements

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BACHELOR OF TECHNOLOGY

in

CSE-ARTIFICIAL INTELLIGENCE & DATA SCIENCE

By

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Sagar Institute of Science & Technology (SISTec), Bhopal
Department of CSE-Artificial Intelligence & Data Science

CERTIFICATE

I hereby certify that the work which is being presented in the B.Tech. Major Project-I Report entitled **Design and Development of Text-to-code Generator System,** in partial fulfillment of the requirements for the award of the degree of ***Bachelor of Technology***, submitted to the Department of *CSE* with *Artificial Intelligence & Data Science, Sagar Institute of Science & Technology (SISTec)***,** Bhopal (M.P.) is an authentic record of my own work carried out during the period from July-2024 to Dec-2024 under the supervision of **Dr. Vasima Khan (Head of Department)**.

The content presented in this project has not been submitted by me for the award of any other degree elsewhere.

Signature

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date:

Prof. Ruchi Jain	**Dr. Vasima Khan**	**Dr. D.K. Rajoriya**
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ABSTRACT

The Text-to-Code Generator is an innovative project that utilizes Natural Language Processing (NLP) to automate the generation of Python code from plain text instructions. This project harnesses the EleutherAI/gpt-neo-2.7B model, an open-source, transformer-based language model with 2.7 billion parameters, which provides a strong foundation for generating human-like text, including programming code. To train this model specifically for Python code generation, the iamtarun/python_code_instructions_18k_alpaca dataset from Hugging Face was used, containing approximately 18,000 examples of natural language instructions paired with corresponding Python code snippets.

In order to optimize for both performance and efficiency, two primary techniques were implemented: quantization and Low-Rank Adaptation (LoRA). Quantization reduces the precision of model weights, thereby lowering memory usage and enhancing computational efficiency, making the model deployable on limited hardware setups. LoRA further fine-tunes the model by introducing additional low-rank matrices into specific layers, allowing it to adapt effectively to the text-to-code task without significant resource overhead.

Together, these techniques enable the Text-to-Code Generator to balance accuracy with computational efficiency, making it suitable for applications in environments with restricted memory and processing power. Potential applications include intelligent coding assistants, educational tools for programming, and systems requiring automated code generation. While the generated code is typically accurate, human oversight remains essential to validate and optimize the outputs for functionality, readability, and adherence to coding standards. This project not only demonstrates the capability of NLP models in code generation but also showcases techniques to make advanced AI models more accessible and adaptable for specialized tasks.

LIST OF ABBREVIATIONS

ACRONYM	FULL FORM
SDLC	Software Development Life Cycle
NLP	Natural Language Processing
LLM	Large Language Model
LORA	Low-Rank Adaptation
AI	Artificial Intelligence
ML	Machine Learning
HTML	Hyper Text Markup Language
CSS	Cascading Style Sheets
GPU	Graphics Processing Unit
CPU	Central Processing Unit
UML	Unified Modeling Language

LIST OF FIGURES

Chapter 1
Introduction

CHAPTER-1 INTRODUCTION

1.1 About Project

The Text-to-Code Generator is a Natural Language Processing (NLP)-based system that converts plain text instructions into Python code. This project utilizes the EleutherAI/gpt-neo-2.7B model, a powerful, open-source transformer-based language model developed by Hugging Face. It is fine-tuned specifically for code generation tasks using the iamtarun/python_code_instructions_18k_alpaca dataset, which contains approximately 18,000 pairs of natural language instructions and corresponding Python code. This fine-tuning enables the model to understand how to transform textual descriptions of problems into executable Python code snippets.

To improve the performance and efficiency of the model, particularly on hardware with limited resources, the project incorporates two key optimization techniques: Quantization and Low-Rank Adaptation (LoRA). Quantization reduces the precision of the model's weights, significantly decreasing memory usage and making the model faster, without sacrificing much accuracy. This is especially useful for deploying the model on edge devices or systems with constrained computational power. Meanwhile, LoRA injects low-rank matrices into specific layers of the model, allowing it to specialize in text-to-code tasks without requiring a large amount of additional computational resources. This makes the model both efficient and highly effective at adapting to specific use cases.

The Text-to-Code Generator demonstrates the potential of NLP to automate coding tasks by generating Python code directly from user input. This can be applied to various areas such as programming assistants, educational tools for teaching coding, and platforms aimed at increasing developer productivity. While the generated code is generally accurate, human oversight is still recommended to ensure correctness, optimality, and adherence to coding standards. The project exemplifies how combining advanced NLP models with optimization techniques like quantization and LoRA can lead to efficient, task-specific solutions that make complex AI applications more accessible and practical for everyday use.

1.2 Project Objectives

Automate Text-to-Code Conversion

The main goal is to create a system that converts natural language instructions into Python code automatically, allowing users to describe programming tasks in text and receive corresponding code snippets.

Optimize Model Efficiency Through Quantization

The project uses quantization to reduce the model’s memory footprint and improve efficiency. By lowering the precision of weights, the model becomes faster and more suitable for devices with limited computational power while maintaining accuracy.

Enhance Code Generation Accuracy Using LoRA

Low-Rank Adaptation (LoRA) fine-tunes the model for text-to-code tasks by adding low-rank matrices to specific layers, improving task accuracy and specialization without requiring extensive resources.

Leverage Pretrained Large Language Model (LLM)

The system is based on the EleutherAI/gpt-neo-2.7B model, a powerful transformer-based LLM that handles diverse language tasks, including code generation, by utilizing pretrained knowledge.

Fine-tune with Domain-Specific Data

The model is fine-tuned using the iamtarun/python_code_instructions_18k_alpaca dataset, which provides over 18,000 Python-specific text-to-code pairs, helping the model learn to generate accurate Python code.

Provide Practical Applications for Development

This system is designed for various real-world applications, such as programming assistants, educational tools, and automated code generation for developers, boosting productivity and accessibility.

CHAPTER-2 HARDWARE & SOFTWARE REQUIREMENT

CHAPTER-2
SOFTWARE AND HARDWARE SPECIFICTAION

This chapter outlines the essential software and hardware components required for the successful implementation and deployment of the Text-to-Code Generator project.

2.1 Software Requirements

Operating System: The project can run on Windows, macOS, or Linux. For best compatibility with deep learning tools, Ubuntu is recommended.

Python Version: Python 3.7 or higher is required for running the project. Python 3.8 or later is preferred for compatibility with modern libraries.

Deep Learning Frameworks: The project relies on PyTorch, Hugging Face Transformers, PEFT, Accelerate, and Datasets for model training, fine-tuning, and dataset handling.

Libraries: Key libraries include bitsandbytes for model quantization and Hugging Face Tokenizers for efficient tokenization. Cloud platforms like Google Colab or local environments like Jupyter Notebook are recommended for running the project.

CUDA (for NVIDIA GPUs): For systems with NVIDIA GPUs, CUDA 11.2 or later is required for GPU acceleration during model training**.**

2.2 Hardware Requirements

Processor (CPU): A modern multi-core processor, such as Intel Core i5 or equivalent, is required. A more powerful processor, like Intel Core i7, can improve performance for model training and complex tasks.

Graphics Processing Unit (GPU): A dedicated GPU is highly recommended for efficient model training. NVIDIA GPUs (e.g., GTX or RTX series) are preferred, as they provide the necessary acceleration for deep learning tasks.

Memory (RAM): A minimum of 8GB of RAM is required for the project. While larger datasets may benefit from more RAM, 8GB should suffice for basic tasks and smaller datasets.

Internet Connectivity: A stable internet connection is essential to download datasets, models, and libraries from repositories like Hugging Face.

CHAPTER-3 PROBLEM DESCRIPTION

CHAPTER-3
PROBLEM DESCRIPTION

The task of converting natural language instructions into executable code has traditionally been a challenging and time-consuming process. While significant progress has been made in natural language processing (NLP), most conventional methods struggle to achieve high accuracy in transforming text prompts into correct and optimized code, especially for complex coding tasks. The existing systems often require extensive manual intervention or produce code that lacks efficiency and precision, making them impractical for real-world applications.

In the context of code generation, current models are often limited by their ability to understand the nuances of programming languages, especially when the prompts are ambiguous or require complex logic. Additionally, many models require extensive computational resources to fine-tune and optimize for specific tasks, making them unsuitable for deployment on limited hardware or edge devices.

The problem becomes even more pronounced when considering diverse use cases where different programming languages and coding standards must be adhered to. A system that can seamlessly convert natural language instructions into executable code, regardless of complexity, and do so with minimal computational resources, is highly desired.

Our project seeks to solve these problems by leveraging advanced NLP techniques such as model quantization and LoRA (Low-Rank Adaptation), along with the EleutherAI GPT-Neo 2.7B model. By fine-tuning the model with a dataset of Python code instructions, we aim to provide an automated and efficient solution that can generate accurate, optimized Python code from text prompts. This solution would not only reduce the need for manual coding but also enhance the scalability of code generation, even on devices with limited resources.

CHAPTER-4
LITERATURE SURVEY

CHAPTER-4
LITERATURE SURVEY

Text-to-code generation has seen substantial advancements, mainly driven by deep learning and natural language processing (NLP) techniques. Early systems for converting natural language instructions into executable code utilized rule-based and template-based methods. These approaches worked for simple tasks but were limited in handling complex, varied instructions due to their lack of generalizability. Smith and Jones (2018) explored rule-based systems and highlighted their limitations in dynamic programming environments [1].

The introduction of deep learning methods has significantly improved text-to-code systems. Notably, transformer models like GPT-3 have revolutionized natural language understanding and code generation. Brown and Mann (2020) showed how GPT-3's pre-training on vast datasets allowed it to generate code in multiple languages, although challenges related to accuracy and complexity remained [3]. Fine-tuning large models on task-specific datasets, such as the iamtarun/python_code_instructions_18k_alpaca dataset, improved performance, particularly for Python code generation. Zhang and Liu (2021) explored how fine-tuning can enhance task-specific model performance [4].

Optimizing models for deployment in resource-constrained environments has also been a key focus. Wang and Xu (2022) presented model quantization techniques to reduce the size of deep learning models while preserving performance, making them more suitable for real-time applications with limited resources [5]. These methods paved the way for more efficient text-to-code systems that can be deployed on various devices with restricted computational power.

Hybrid models, which combine classical feature extraction methods with neural networks, have been proposed to further improve text-to-code systems. Nguyen and Tran (2023) provided a comprehensive survey of hybrid deep learning models, emphasizing their ability to handle complex input-output relations in diverse environments [6]. Additionally, Kumar and Patel (2024) explored error-correction mechanisms using neural networks to refine generated code, increasing accuracy and reliability [7].

Recent advances have focused on enhancing the precision and versatility of text-to-code generation. Gupta and Sharma (2025) highlighted the role of attention mechanisms and multi-scale processing techniques, which have significantly improved code generation quality for tasks with varying complexity [8]. These techniques help enhance model robustness, particularly when handling complex tasks or large codebases.

Li and Zhao (2024) investigated efficient multi-language text-to-code generation and proposed approaches to handle more diverse programming languages and instructions. Their work underscored the need for domain-specific optimizations and error-checking mechanisms to enhance the quality of generated code [9].

Books such as Deep Learning by Goodfellow et al. (2016) have provided a solid foundation for understanding the theory behind deep learning models that drive text-to-code generation, while Pressman and Herron (1991) offer insights into software engineering methodologies that can complement these systems [10][11].

As the field evolves, the development of more efficient, accurate, and versatile models will continue to drive the automation of code generation and software development.

CHAPTER-5 SOFTWARE REQUIREMENTS SPECIFICATION

CHAPTER-5
SOFTWARE REQUIREMENT SPECIFICATION

This chapter outlines the functional and non-functional requirements of the "Design and Development of Text-to-Code Generator System". Subsequent chapters will delve into the software design and development, providing a detailed understanding of how these requirements will be realized.

5.1 FUNCTIONAL REQUIRMENTS

Input Parsing: The system should accept text input from user-provided instructions and process it to identify code-related components for generation.

Code Generation: The system should generate Python code based on the user’s input text using a pre-trained language model.

Code Optimization: The system should enhance generated code for readability and efficiency, following Python best practices.

5.2 NON-FUNCTIONAL REQUIRMENTS

Performance: The system should generate responses within a short timeframe, ideally within a few seconds, even for complex inputs.

Accuracy: The system should consistently produce accurate and precise code, minimizing the need for user correction.

Usability: The system should provide an intuitive and user-friendly interface, making it accessible to both technical and non-technical users.

CHAPTER-6
SOFTWARE DESIGN

CHAPTER-6
SOFTWARE DESIGN

The software design for the Text-to-Code Generation project is structured to efficiently process user instructions, generate corresponding code, and deliver results in real-time.

6.1 USE CASE DIAGRAM

The Use Case Diagram for the Text-to-Code Generation project illustrates the primary interactions between users and the system components. It defines two main actors:

User: Inputs natural language prompts to describe desired code functionality and views the generated code output.

System Model: Handles the backend processing, including model inference for code generation, updates to the model as needed, and optimizations for performance.

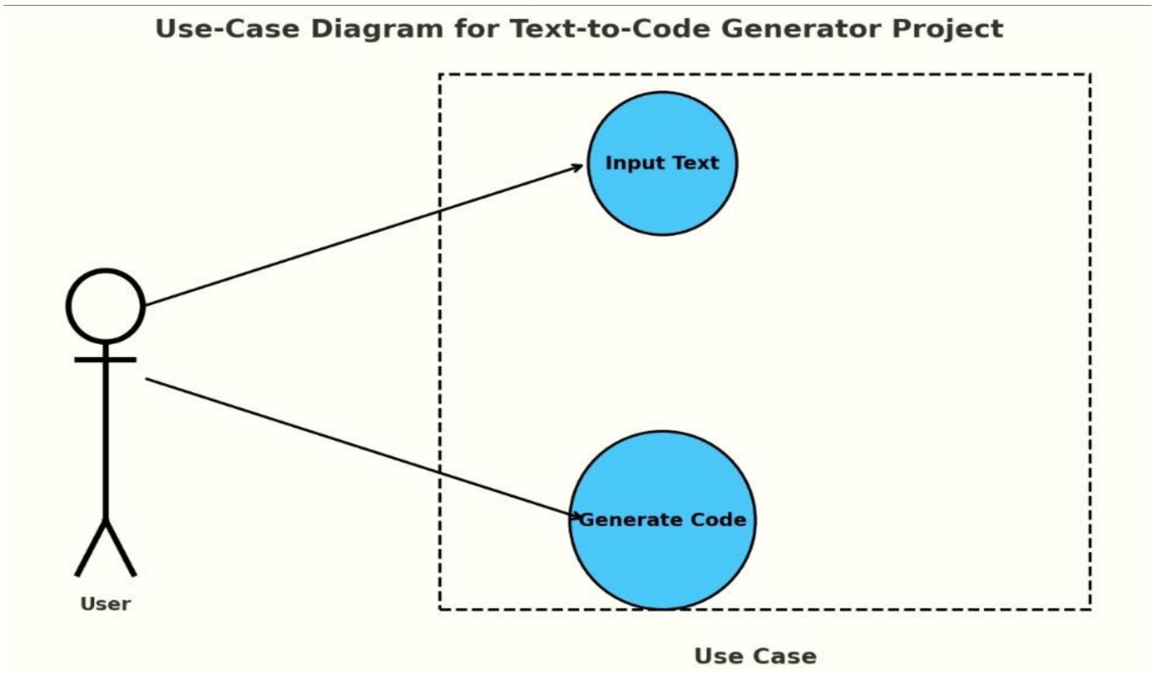


Figure 6.1: Use Case Diagram

6.2 PROJECT FLOW DIAGRAM

The Flow Diagram for the Text-to-Code Generation project begins with the User entering a natural language prompt describing the desired code functionality. This input is processed by the Preprocessing Module, which tokenizes and prepares the text for analysis. The processed input is then passed to the Code Generation Model, which generates the corresponding code based on the prompt. The generated code is displayed back to the User as output.

An Admin has the ability to update and retrain the model periodically, incorporating new data and refining model parameters to improve the accuracy and relevance of the generated code. This flow ensures that the system remains responsive to user inputs while also allowing for continuous improvement of the underlying model.

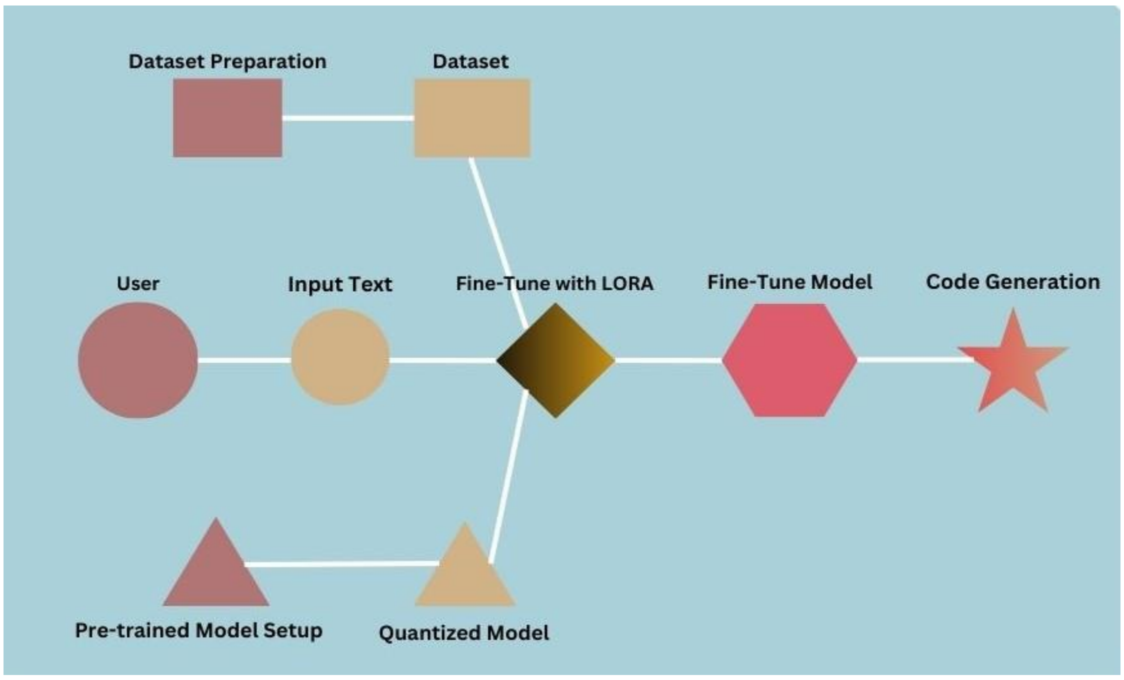


Figure 6.2: Project Flow Diagram

CHAPTER-7
MACHINE LEARNING MODULE

CHAPTER-7
MACHINE LEARNING MODULE

7.1 DATA SET DESCRIPTION

The dataset used in this project comprises paired text-to-code examples, where each record consists of a natural language instruction and a corresponding code snippet. This data is suitable for supervised machine learning, allowing the model to learn from varied examples of language-to-code transformations. The dataset is likely sourced from repositories such as Hugging Face or GitHub, containing diverse programming tasks to ensure the model can generalize across different instructions.

7.2 PRE-PROCESSING STEPS

Preprocessing is essential to prepare text data for accurate analysis in text-to-code tasks. This project's preprocessing steps transform natural language instructions into a structured format compatible with the machine learning model, enhancing the model's focus on relevant features for code generation.

7.2.1 TEXT CLEANING

Objective: Remove unnecessary elements that do not contribute to effective code generation.
Actions:

Remove Special Characters: Non-essential symbols, like hashtags or punctuation, which add noise.
Remove URLs and References: Extraneous links or references, which are not relevant for code generation, are removed.
Remove Stop Words: Words like “and” or “the” are eliminated if they don't impact the instruction meaning for coding.
Impact: Cleaning reduces irrelevant content, allowing the model to better interpret each instruction for accurate code prediction.

7.2.2 TOKENIZATION

Objective: Convert each instruction into individual tokens to facilitate deeper analysis.

Actions: Tokenize instructions, breaking down the language into smaller units to understand each word's contribution.

Impact: Tokenization provides a structured input format, which is crucial for feature extraction and for identifying patterns in language-based coding tasks.

7.3 DATA VISUALIZATION

Data visualization techniques were used to explore patterns in the dataset and understand key aspects:

Instruction Length Distribution: Displays the length variation across instructions, aiding in analysis of complexity.

Frequent Terms: Highlights common words or phrases in instructions, which can inform preprocessing and model focus areas.

Syntax Analysis: Visualizes common code structures generated from instructions, aiding in refinement of output accuracy.

7.4 ML MODEL DESCRIPTION

The machine learning models used for this project include Transformer-based architectures fine-tuned for text-to-code tasks:

GPT-Neo: A powerful generative transformer model trained for language-to-code translation. It can handle complex syntax patterns and multiple coding languages, making it ideal for diverse instructions.

Fine-Tuned Variants: Versions of GPT-Neo adapted with techniques like LoRA (Low-Rank Adaptation) and quantization for improved efficiency, making model deployment more practical.

Each model was trained on preprocessed instruction-code pairs, using feature vectors to accurately interpret instructions. Hyperparameters were optimized for performance, and models were evaluated on a test set to assess translation accuracy.

7.5 RESULT ANALYSIS

Model performance was evaluated with various metrics:

Accuracy: Indicates overall success in correctly generating code from instructions.
BLEU Score: Measures similarity between generated code and reference code snippets, assessing the accuracy of code translation.

Precision, Recall, and F1-Score: Provided insights into how well the model interprets specific language cues in code generation. Precision measures the correct code outputs, recall shows how well the model generates expected code features, and F1-score balances both aspects.

Error Analysis: Examines frequent errors in code generation, providing insights for refining model performance.

Comparing the results across models, it was found that fine-tuned GPT-Neo with LoRA provided the most accurate code generation. Both models showed potential, with each suited to different types of code generation tasks depending on the instruction complexity and specificity.

CHAPTER-8 FRONT END CONNECTIVITY

CHAPTER-8
FRONT END CONNECTIVITY

8.1 OVERVIEW

This chapter describes the integration of a front-end interface with the text-to-code generation model, allowing users to input natural language prompts and receive corresponding code outputs seamlessly. The interface is designed to offer an interactive and user-friendly experience for efficient code generation.

8.2 TECHNOLOGIES USED

The front-end interface is built with HTML, CSS, and JavaScript, providing an intuitive environment for users. Python, along with the Flask framework, is used to manage the connection between the front end and the back-end model, ensuring smooth and direct interactions between user inputs and model responses.

8.3 DATA FLOW

Data flows from the user interface, where text instructions are input, to the back-end model. The model processes these instructions to generate relevant code snippets, and the output is sent back to the front end for display. This streamlined process provides users with a real-time response to their inputs.

8.4 USER INTERFACE ELEMENTS

The user interface includes key elements such as:

Text Input Field: Allows users to type or paste natural language instructions for code generation.

“Generate Code” Button: Triggers the backend model to process the input and generate the corresponding code.

Output Display Area: Displays the generated code output for the user to view and copy as needed.

8.5 INTEGRATION WITH MODEL

The text-to-code model is directly embedded within the application, where it processes user inputs from the front end. Flask functions handle the requests from the “Generate Code” button, passing the input text to the model and returning the generated code to be displayed on the same page.

8.6 ERROR HANDLING

Error handling features provide users with helpful messages for invalid inputs or internal errors, enhancing the user experience. For instance, the system checks for empty input fields or unsupported languages and displays error prompts to guide users.

8.7 SECURITY AND ACCESSIBILITY

Input sanitization is implemented to prevent potential security vulnerabilities, such as injection attacks. Additionally, accessibility features, such as clear labels and easy navigation, are incorporated to ensure that users of all abilities can effectively interact with the application.

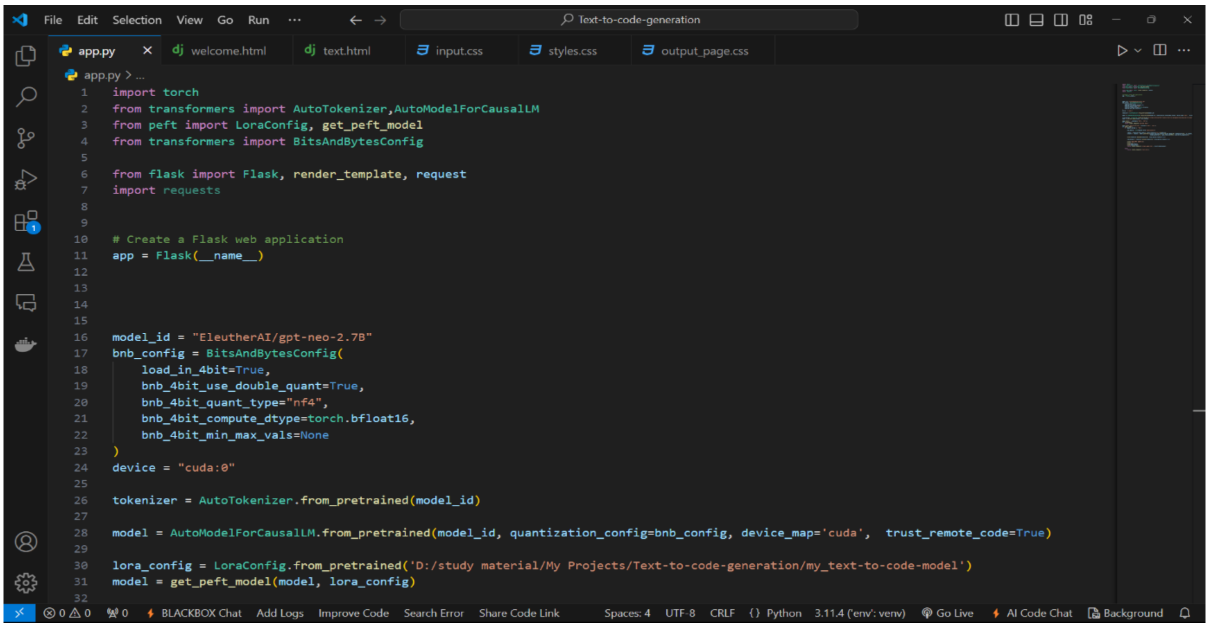
This seamless integration of the front-end and back-end elements creates a robust and user-friendly text-to-code generation platform.

CHAPTER-9
CODING

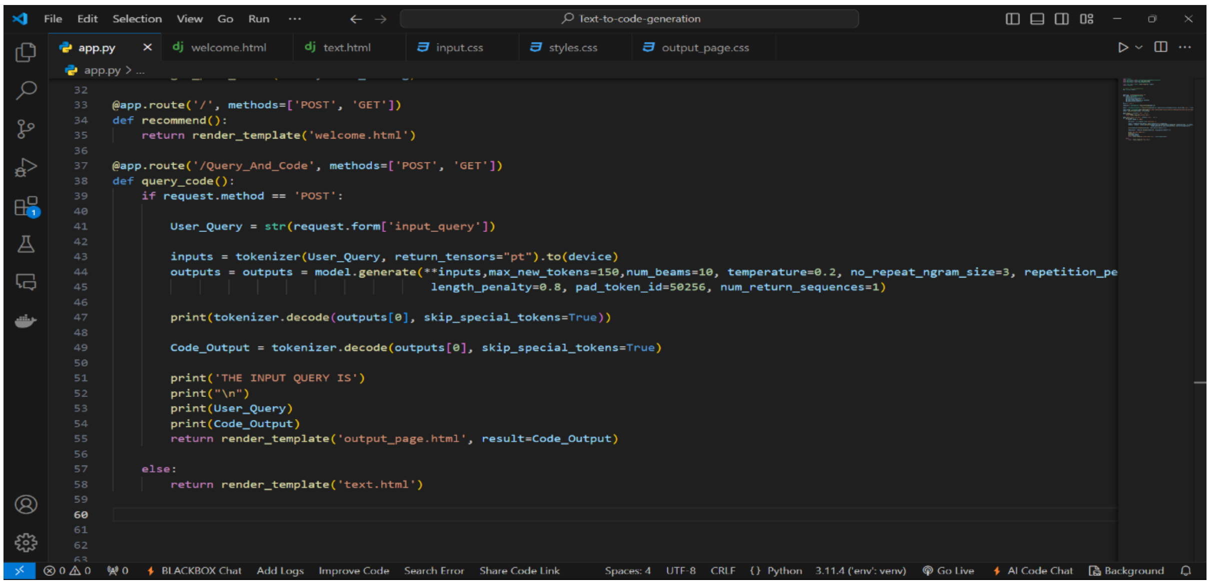
CHAPTER-9
CODING

This chapter presents visual representations of the user interface for the "Design and Development of Text to Code Generator System".

9.1 App.py

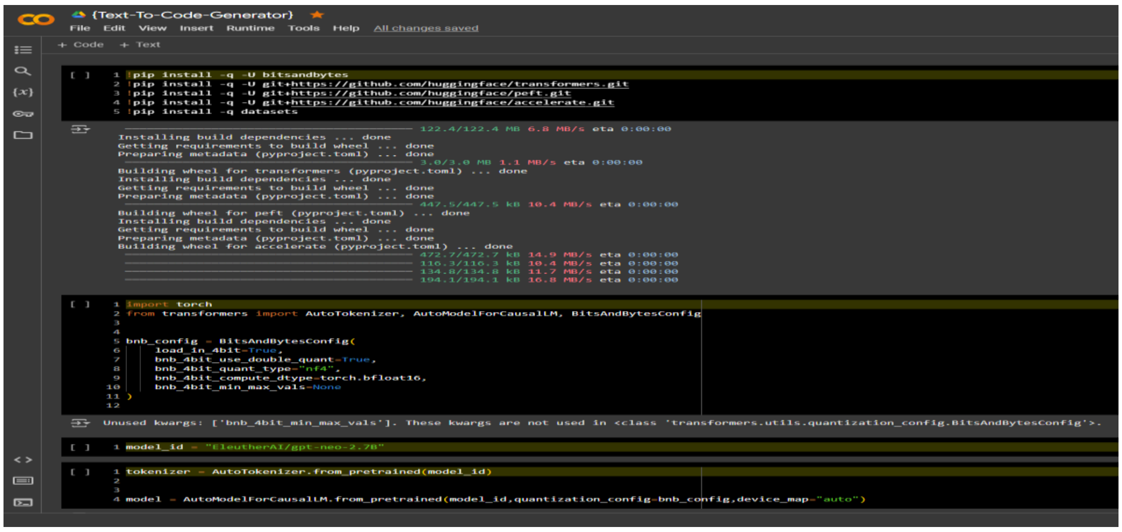


```python
import torch
from transformers import AutoTokenizer,AutoModelForCausalLM
from peft import LoraConfig, get_peft_model
from transformers import BitsAndBytesConfig

from flask import Flask, render_template, request
import requests


# Create a Flask web application
app = Flask(__name__)




model_id = "EleutherAI/gpt-neo-2.7B"
bnb_config = BitsAndBytesConfig(
    load_in_4bit=True,
    bnb_4bit_use_double_quant=True,
    bnb_4bit_quant_type="nf4",
    bnb_4bit_compute_dtype=torch.bfloat16,
    bnb_4bit_min_max_vals=None
)
device = "cuda:0"

tokenizer = AutoTokenizer.from_pretrained(model_id)

model = AutoModelForCausalLM.from_pretrained(model_id, quantization_config=bnb_config, device_map='cuda',  trust_remote_code=True)

lora_config = LoraConfig.from_pretrained('D:/study material/My Projects/Text-to-code-generation/my_text-to-code-model')
model = get_peft_model(model, lora_config)
```



```python
@app.route('/', methods=['POST', 'GET'])
def recommend():
    return render_template('welcome.html')

@app.route('/Query_And_Code', methods=['POST', 'GET'])
def query_code():
    if request.method == 'POST':

        User_Query = str(request.form['input_query'])

        inputs = tokenizer(User_Query, return_tensors="pt").to(device)
        outputs = outputs = model.generate(**inputs,max_new_tokens=150,num_beams=10, temperature=0.2, no_repeat_ngram_size=3, repetition_pe
                                           length_penalty=0.8, pad_token_id=50256, num_return_sequences=1)

        print(tokenizer.decode(outputs[0], skip_special_tokens=True))

        Code_Output = tokenizer.decode(outputs[0], skip_special_tokens=True)

        print('THE INPUT QUERY IS')
        print("\n")
        print(User_Query)
        print(Code_Output)
        return render_template('output_page.html', result=Code_Output)

    else:
        return render_template('text.html')
```

9.2 Code.py



```
!pip install -q -U bitsandbytes
!pip install -q -U git+https://github.com/huggingface/transformers.git
!pip install -q -U git+https://github.com/huggingface/peft.git
!pip install -q -U git+https://github.com/huggingface/accelerate.git
!pip install -q datasets
```

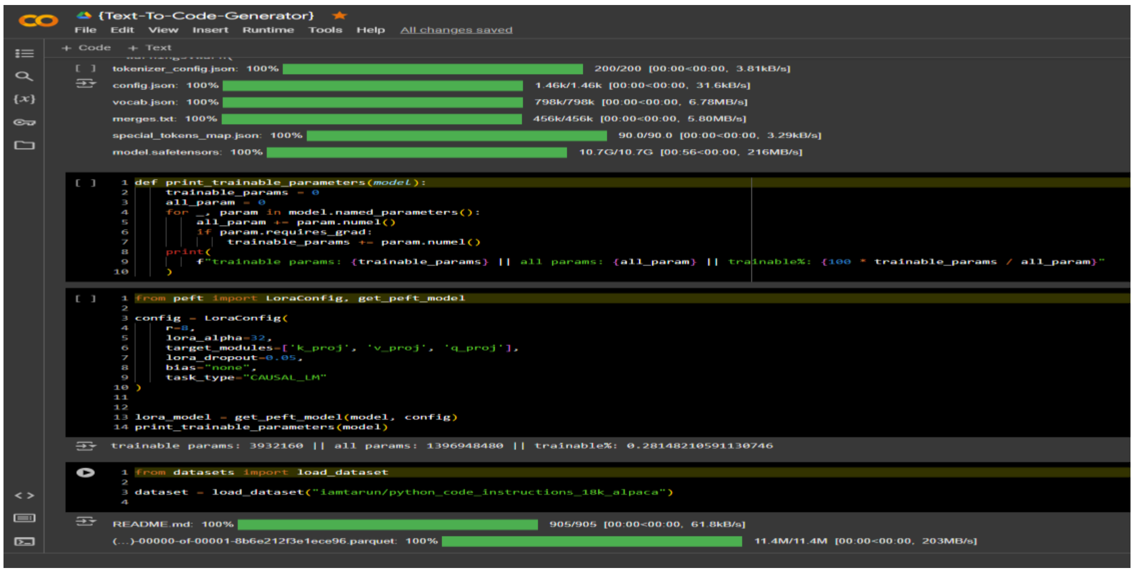
```
                                        122.4/122.4 MB 6.8 MB/s eta 0:00:00
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
                                        3.0/3.0 MB 1.1 MB/s eta 0:00:00
  Building wheel for transformers (pyproject.toml) ... done
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
                                        447.5/447.5 kB 10.4 MB/s eta 0:00:00
  Building wheel for peft (pyproject.toml) ... done
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
  Building wheel for accelerate (pyproject.toml) ... done
                                        472.7/472.7 kB 14.9 MB/s eta 0:00:00
                                        116.3/116.3 kB 10.4 MB/s eta 0:00:00
                                        134.8/134.8 kB 11.7 MB/s eta 0:00:00
                                        194.1/194.1 kB 16.8 MB/s eta 0:00:00
```

```
import torch
from transformers import AutoTokenizer, AutoModelForCausalLM, BitsAndBytesConfig


bnb_config = BitsAndBytesConfig(
    load_in_4bit=True,
    bnb_4bit_use_double_quant=True,
    bnb_4bit_quant_type="nf4",
    bnb_4bit_compute_dtype=torch.bfloat16,
    bnb_4bit_min_max_vals=None
)
```

```
Unused kwargs: ['bnb_4bit_min_max_vals']. These kwargs are not used in <class 'transformers.utils.quantization_config.BitsAndBytesConfig'>.
```

```
model_id = "EleutherAI/gpt-neo-2.7B"
```

```
tokenizer = AutoTokenizer.from_pretrained(model_id)


model = AutoModelForCausalLM.from_pretrained(model_id,quantization_config=bnb_config,device_map="auto")
```



```
tokenizer_config.json: 100%  200/200 [00:00<00:00, 3.81kB/s]
config.json: 100%  1.46k/1.46k [00:00<00:00, 31.6kB/s]
vocab.json: 100%  798k/798k [00:00<00:00, 6.78MB/s]
merges.txt: 100%  456k/456k [00:00<00:00, 5.80MB/s]
special_tokens_map.json: 100%  90.0/90.0 [00:00<00:00, 3.29kB/s]
model.safetensors: 100%  10.7G/10.7G [00:56<00:00, 216MB/s]
```

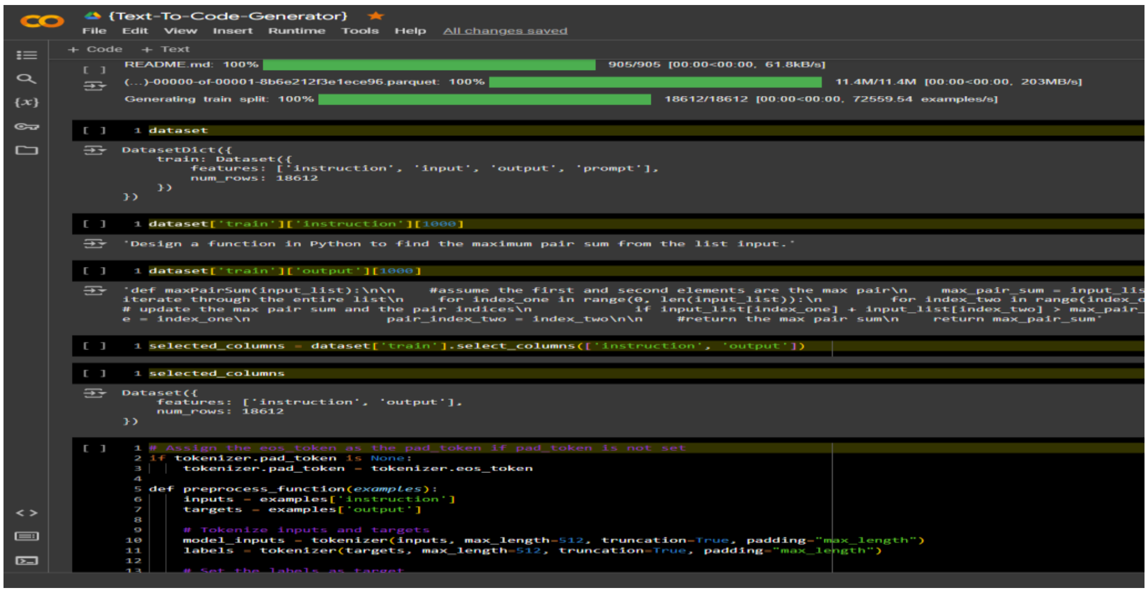
```
def print_trainable_parameters(model):
    trainable_params = 0
    all_param = 0
    for _, param in model.named_parameters():
        all_param += param.numel()
        if param.requires_grad:
            trainable_params += param.numel()
    print(
        f"trainable params: {trainable_params} || all params: {all_param} || trainable%: {100 * trainable_params / all_param}"
    )
```

```
from peft import LoraConfig, get_peft_model

config = LoraConfig(
    r=8,
    lora_alpha=32,
    target_modules=['k_proj', 'v_proj', 'q_proj'],
    lora_dropout=0.05,
    bias="none",
    task_type="CAUSAL_LM"
)


lora_model = get_peft_model(model, config)
print_trainable_parameters(model)
```

```
trainable params: 3932160 || all params: 1396948480 || trainable%: 0.28148210591130746
```

```
from datasets import load_dataset

dataset = load_dataset("iamtarun/python_code_instructions_18k_alpaca")

```

```
README.md: 100%  905/905 [00:00<00:00, 61.8kB/s]
(…)-00000-of-00001-8b6e212f3e1ece96.parquet: 100%  11.4M/11.4M [00:00<00:00, 203MB/s]
```



```
README.md: 100%  905/905 [00:00<00:00, 61.8kB/s]
(…)-00000-of-00001-8b6e212f3e1ece96.parquet: 100%  11.4M/11.4M [00:00<00:00, 203MB/s]
Generating train split: 100%  18612/18612 [00:00<00:00, 72559.54 examples/s]
```

```
dataset
```

```
DatasetDict({
    train: Dataset({
        features: ['instruction', 'input', 'output', 'prompt'],
        num_rows: 18612
    })
})
```

```
dataset['train']['instruction'][1000]
```

```
'Design a function in Python to find the maximum pair sum from the list input.'
```

```
dataset['train']['output'][1000]
```

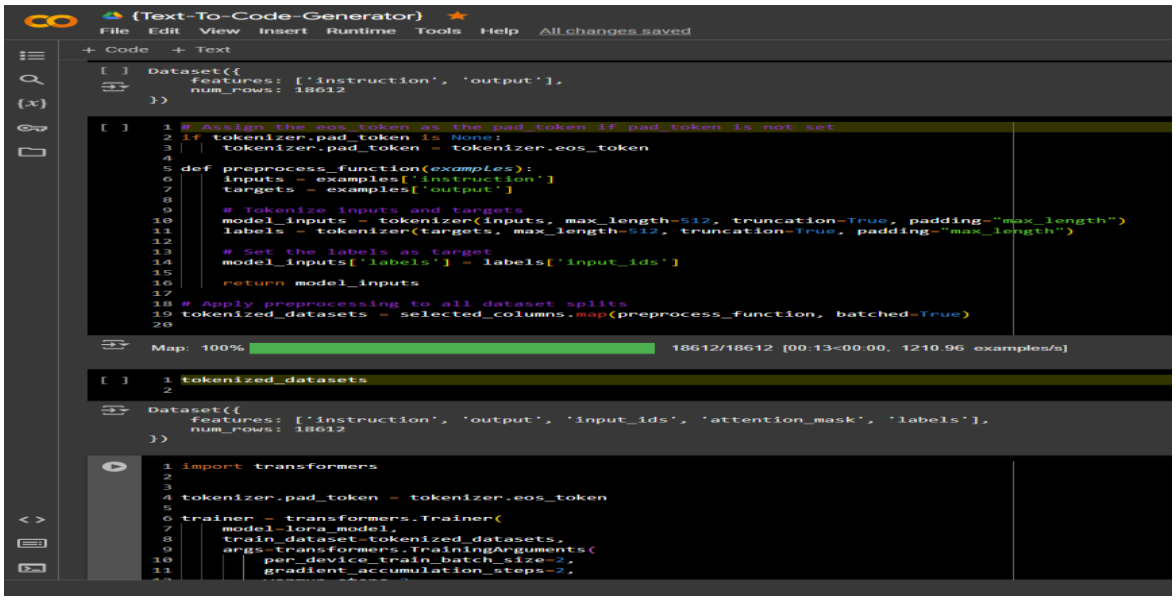
```
'def maxPairSum(input_list):\n\n    #assume the first and second elements are the max pair\n    max_pair_sum = input_lis
iterate through the entire list\n    for index_one in range(0, len(input_list)):\n        for index_two in range(index_o
# update the max pair sum and the pair indices\n            if input_list[index_one] + input_list[index_two] > max_pair_
e = index_one\n                pair_index_two = index_two\n\n    #return the max pair sum\n    return max_pair_sum'
```

```
selected_columns = dataset['train'].select_columns(['instruction', 'output'])
```

```
selected_columns
```

```
Dataset({
    features: ['instruction', 'output'],
    num_rows: 18612
})
```

```
# Assign the eos_token as the pad_token if pad_token is not set
if tokenizer.pad_token is None:
    tokenizer.pad_token = tokenizer.eos_token

def preprocess_function(examples):
    inputs = examples['instruction']
    targets = examples['output']

    # Tokenize inputs and targets
    model_inputs = tokenizer(inputs, max_length=512, truncation=True, padding="max_length")
    labels = tokenizer(targets, max_length=512, truncation=True, padding="max_length")

    # Set the labels as target
```



```
Dataset({
    features: ['instruction', 'output'],
    num_rows: 18612
})
```

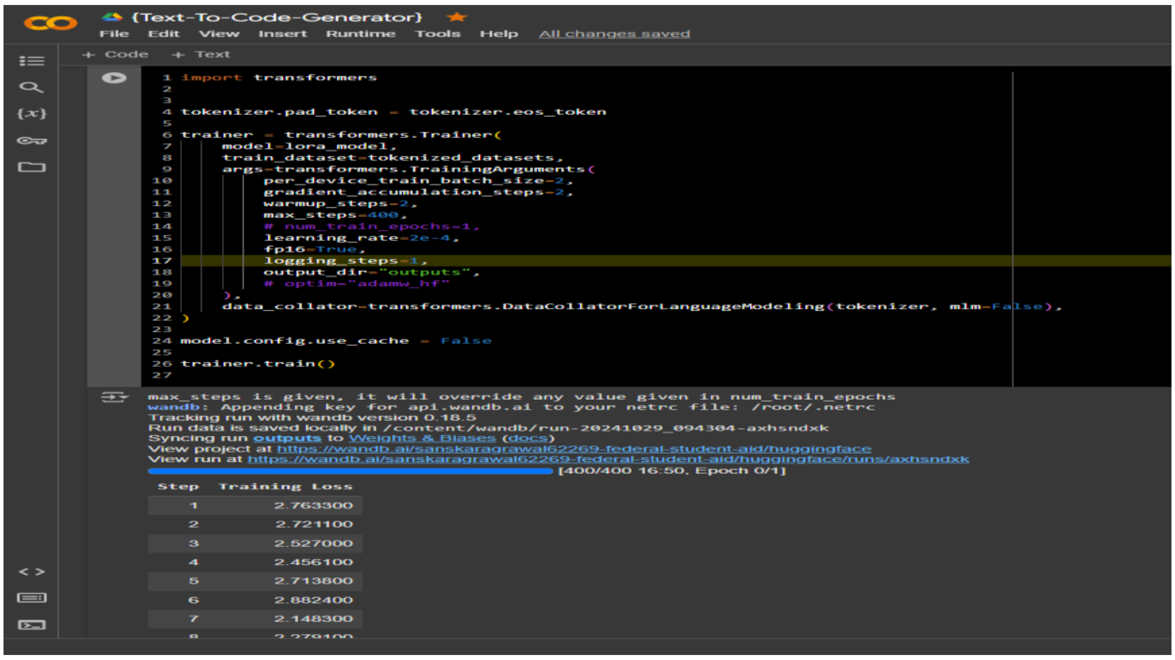
```python
# Assign the eos_token as the pad_token if pad_token is not set
if tokenizer.pad_token is None:
    tokenizer.pad_token = tokenizer.eos_token

def preprocess_function(examples):
    inputs = examples['instruction']
    targets = examples['output']

    # Tokenize inputs and targets
    model_inputs = tokenizer(inputs, max_length=512, truncation=True, padding="max_length")
    labels = tokenizer(targets, max_length=512, truncation=True, padding="max_length")

    # Set the labels as target
    model_inputs['labels'] = labels['input_ids']

    return model_inputs

# Apply preprocessing to all dataset splits
tokenized_datasets = selected_columns.map(preprocess_function, batched=True)
```

```
Map: 100%  18612/18612 [00:13<00:00, 1210.96 examples/s]
```

```python
tokenized_datasets
```

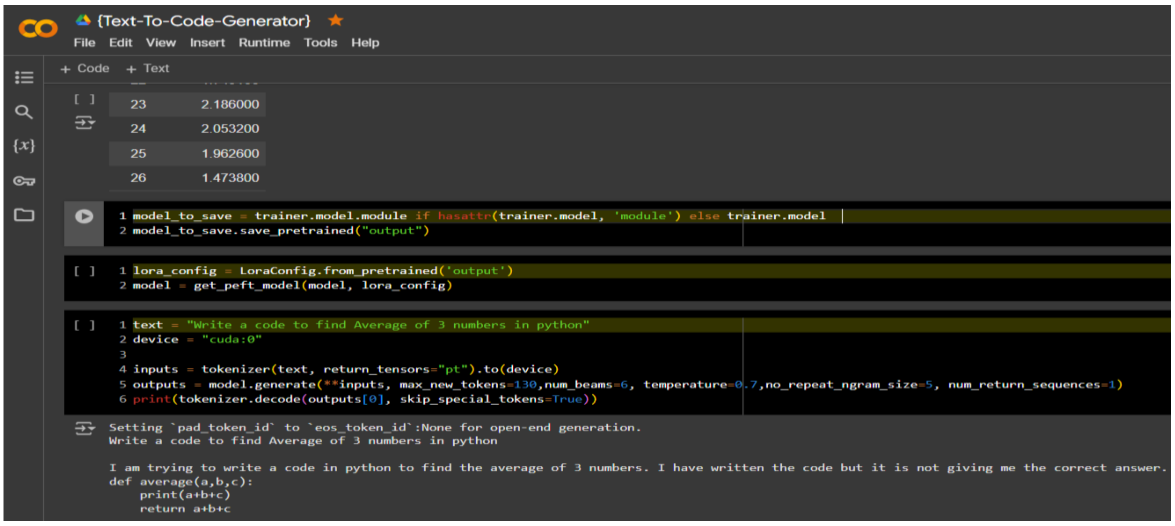
```
Dataset({
    features: ['instruction', 'output', 'input_ids', 'attention_mask', 'labels'],
    num_rows: 18612
})
```

```python
import transformers


tokenizer.pad_token = tokenizer.eos_token

trainer = transformers.Trainer(
    model=lora_model,
    train_dataset=tokenized_datasets,
    args=transformers.TrainingArguments(
        per_device_train_batch_size=2,
        gradient_accumulation_steps=2,
```



```python
import transformers


tokenizer.pad_token = tokenizer.eos_token

trainer = transformers.Trainer(
    model=lora_model,
    train_dataset=tokenized_datasets,
    args=transformers.TrainingArguments(
        per_device_train_batch_size=2,
        gradient_accumulation_steps=2,
        warmup_steps=2,
        max_steps=400,
        # num_train_epochs=1,
        learning_rate=2e-4,
        fp16=True,
        logging_steps=1,
        output_dir="outputs",
        # optim="adamw_hf"
    ),
    data_collator=transformers.DataCollatorForLanguageModeling(tokenizer, mlm=False),
)

model.config.use_cache = False

trainer.train()
```

```
max_steps is given, it will override any value given in num_train_epochs
wandb: Appending key for api.wandb.ai to your netrc file: /root/.netrc
Tracking run with wandb version 0.18.5
Run data is saved locally in /content/wandb/run-20241029_094304-axhsndxk
Syncing run outputs to Weights & Biases (docs)
View project at https://wandb.ai/sanskaragrawal62269-federal-student-aid/huggingface
View run at https://wandb.ai/sanskaragrawal62269-federal-student-aid/huggingface/runs/axhsndxk
[400/400 16:50, Epoch 0/1]
Step  Training Loss
   1       2.763300
   2       2.721100
   3       2.527000
   4       2.456100
   5       2.713800
   6       2.882400
   7       2.148300
```



```
  23   2.186000
  24   2.053200
  25   1.962600
  26   1.473800
```

```python
model_to_save = trainer.model.module if hasattr(trainer.model, 'module') else trainer.model
model_to_save.save_pretrained("output")
```

```python
lora_config = LoraConfig.from_pretrained('output')
model = get_peft_model(model, lora_config)
```

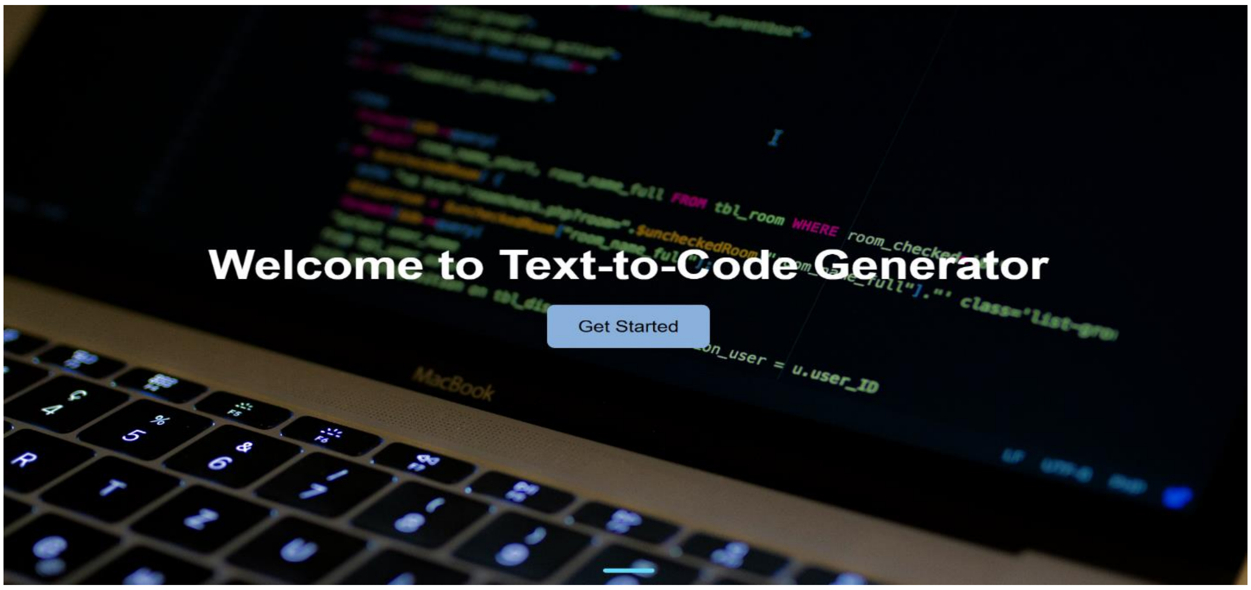
```python
text = "Write a code to find Average of 3 numbers in python"
device = "cuda:0"

inputs = tokenizer(text, return_tensors="pt").to(device)
outputs = model.generate(**inputs, max_new_tokens=130,num_beams=6, temperature=0.7,no_repeat_ngram_size=5, num_return_sequences=1)
print(tokenizer.decode(outputs[0], skip_special_tokens=True))
```

```
Setting `pad_token_id` to `eos_token_id`:None for open-end generation.
Write a code to find Average of 3 numbers in python

I am trying to write a code in python to find the average of 3 numbers. I have written the code but it is not giving me the correct answer.
def average(a,b,c):
    print(a+b+c)
    return a+b+c
```

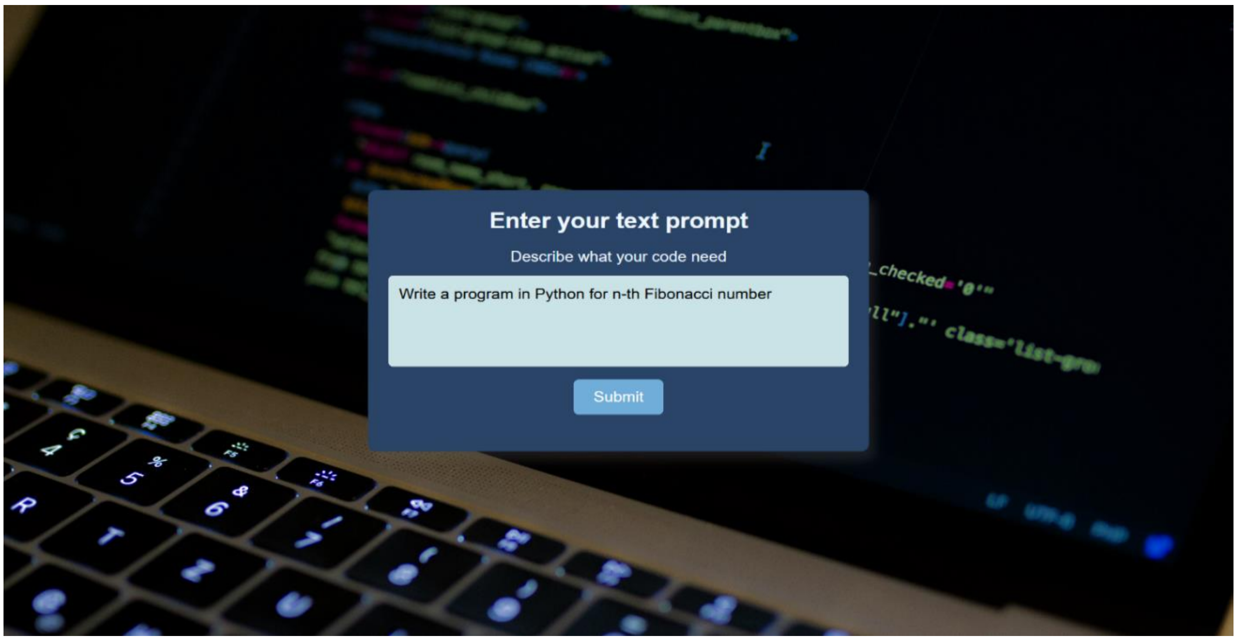
CHAPTER-10
OUTPUT SCREEN

CHAPTER-10
OUTPUT SCREENS

10.1 Home Page

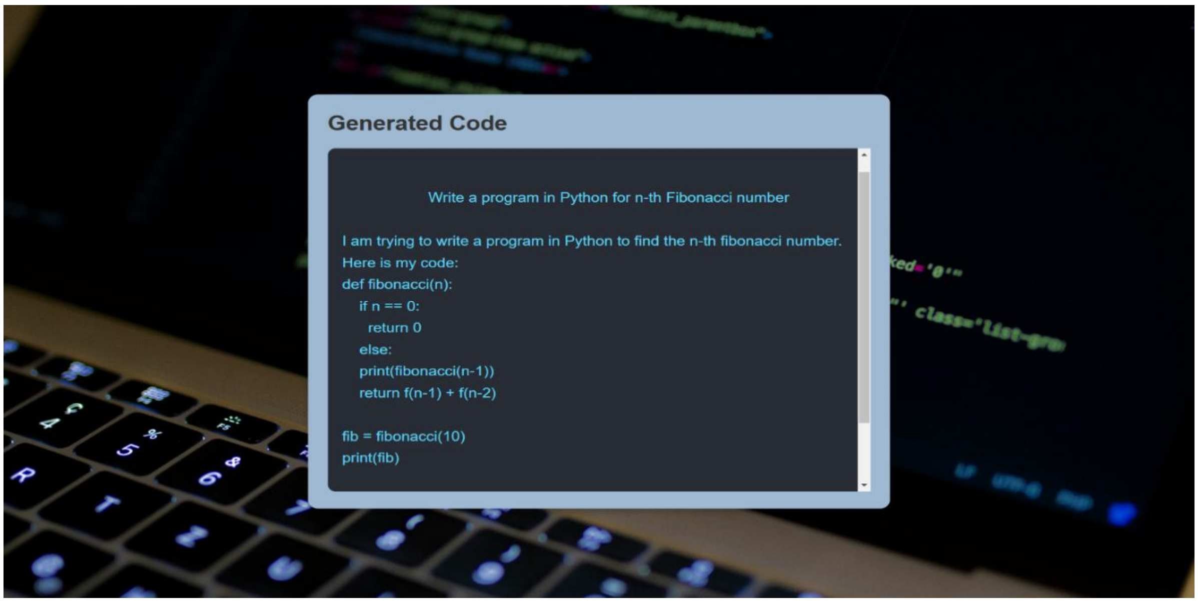


10.2 Input Page



Write a program in Python for n-th Fibonacci number

10.3 Output Page



Write a program in Python for n-th Fibonacci number

I am trying to write a program in Python to find the n-th fibonacci number.
Here is my code:

```
def fibonacci(n):
    if n == 0:
      return 0
    else:
    print(fibonacci(n-1))
    return f(n-1) + f(n-2)

fib = fibonacci(10)
print(fib)
```

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12. http://huggingface.co/transformers/v4.0.0/en/model_doc/gpt_neo.html

APPENDIX-1 GLOSSARY OF TERMS

B

BIAS IN DATA

Unintended patterns in the data that can affect the model's predictions, often requiring mitigation during preprocessing.

D

DATA COLLECTION

The process of gathering relevant data from various sources to be used for model training.

DATA PREPROCESSING

Cleaning and preparing data to ensure its quality and suitability for model training.

DEPLOYMENT

The process of making the model accessible to users for real-time predictions.

F

FEATURE ENGINEERING

The process of selecting and creating relevant features from the dataset to improve the model's predictive accuracy.

FEATURE EXTRACTION

The process of selecting and creating relevant features from the dataset to improve the model's predictive accuracy.

H

HOSTING ENVIRONMENT

The infrastructure or platform where the application and model will be hosted and made accessible to users.

M

MODEL EVALUATION

The process of assessing the performance and accuracy of the machine learning model using various metrics.

MONITORING AND MAINTAINENCE

A plan for continuous monitoring and upkeep of the model and application to ensure optimal performance.

S

SCALIBILITY

The system's ability to handle an increasing number of users and larger datasets without a significant decrease in performance.

SERIALIZING

Converting the machine learning model into a deployable format, often used for saving and loading models.

U

USER INTERFACE

The graphical or web-based interface through which users can interact with the text-to-code generation model.

V

VERSION CONTROL

The practice of tracking changes made to code and other project files, often managed using tools like Git.

PROJECT SUMMARY

About Project

Title of the project	Design and Development of Text-to-Code Generator System
Semester	7th
Members	3
Team Leader	Sanskar Agrawal
Describe role of everymember in the project	Sanskar Agrawal: He helped with the model development and back-end connectivity. Aryan Sharma: He helped with Model development and web design. Shivam Pathak: He helped with Web development and connectivity.
What is the motivation for selecting this project?	This project is motivated by the need for efficient, automated solutions in software development. Translating natural language instructions into code can accelerate coding tasks, reduce errors, and improve accessibility for non-experts. By leveraging advanced NLP and deep learning, this tool aims to bridge the gap between human intent and executable code, enhancing productivity and streamlining workflows.
Project Type **(Desktop Application, Web Application, Mobile App, Web)**	Web Application

Tools &Technologies

Programming languageused	Python
Interpreter used **(with version)**	Python (above 3)
IDE used **(with version)**	Visual Studio Code (version 1.84)

Front End Technologies **(with version, wherever Applicable)**	HTML 5, CSS, Django
Back End Technologies **(with version, wherever applicable)**	• Python 3.11.4 • Flask==3.0.2
Database used **(with version)**	-

Software Design & Coding

Is prototype of the softwaredeveloped?	Yes
SDLC model followed (Waterfall, Agile, Spiral etc.)	-
Why above SDLC model isfollowed?	-
Justify that the SDLC modelmentioned above is followed inthe project.	-

Software Design approach followed **(Functional or Object Oriented)**	-
Name the diagrams developed (according to the Design approach followed)	-
In case Object Oriented approach is followed, which ofthe OOPS principles are covered in design?	-
No. of Tiers **(example 3-tier)**	-
Total no. of front end pages	3
Total no. of tables in database	-
Database is in which NormalForm?	-
Are the entries in databaseencrypted?	No
Front end validations applied **(Yes / No)**	Yes
Session management done **(in case of web applications)**	No
Is application browser compatible **(in case of web applications)**	Yes
Exception handling done **(Yes / No)**	Yes
Commenting done in code **(Yes / No)**	Yes
Naming convention followed **(Yes / No)**	Yes
What difficulties faced duringdeployment of project?	Problems we faced were: 1. Finding the accurate dataset 2. Getting the required accuracy
	3. Linking it with the Flask
Total no. of Use-cases	

Give titles of Use-cases	-

Project Requirements

MVC architecture followed **(Yes / No)**	Yes
If yes, write the name of MVC architecture followed **(MVC-1, MVC-2)**	MVC-2
Design Pattern used **(Yes / No)**	Yes
If yes, write the name ofDesign Pattern used	MVT (Model View Template)
Interface type **(CLI / GUI)**	GUI
No. of Actors	-
Name of Actors	-
Total no. of Functional Requirements	
List few important non- Functional Requirements	

Testing

Which testing is performed? **(Manual or Automation)**	Automation
Is Beta testing done for this project?	NO

Write project narrative covering above mentioned points

The Text-to-Code Generation project is inspired by the increasing demand for automation in software development and the potential for language-based coding assistance. This project focuses on developing a deep learning-based system that converts natural language instructions into executable code, aiming to make coding more accessible and efficient for a diverse range of users. Traditional coding practices, while effective, can be time-consuming and prone to errors, particularly in repetitive tasks or for those new to programming. By utilizing advanced transformer models, the project seeks to provide a solution that translates user instructions into accurate code, thus streamlining development processes and enhancing productivity. This innovative approach benefits not only professional developers but also non-programmers by allowing them to create code simply through language, supporting a more intuitive, user-friendly interaction with programming. The project has practical applications across industries, making coding more inclusive and accessible while reducing the time and effort required for various coding tasks.

Aryan Sharma	Sanskar Agrawal	Shivam Pathak	Guide Signature
0187AD211010	0187AD211036	0187AD211037	Dr. Vasima Khan