**CodeCrafter**

 A Project Report

                        Submitted in the partial fulfillment of the

                          requirements for the award of the degree of

**BACHELOR OF TECHNOLOGY**

**In**

**DEPARTMENT OF COMPUTER SCIENCE ENGINNERING**

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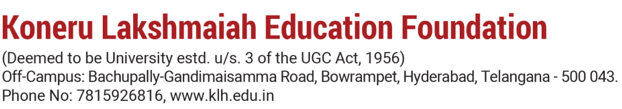
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**Declaration**

The Project Report entitled “**CodeCrafter**“ is a record of Bonafide work of **Dr. P.V. Rao**

**,Manasa Lahari-2320030205,Rishika-2320030471,Gayathri-2320030382** submitted in partial fulfillment for the award of B. Tech in Computer  Engineering to the K L University. The results embodied in this report have not been copied from any other departments/University/Institute.

**Dr. P.V. Rao**

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**DEPARTMENT OF COMPUTER SCIENCE ENGINEERING**



**Certificate**

This is certify that the project based report entitled “**CodeCrafter**” is a bonafide work done and submitted by **Manasa Lahari-2320030205,Rishika-2320030471,Gayathri-2320030382 (** in partial fulfillment of the requirements for the award of the degree of **BACHELOR OF TECHNOLOGY** in Department of Computer Science Engineering, K L (Deemed to be University), during the academic year **2024-2025.**

**Signature of the Supervisor**

**Signature of the HOD                                               Signature of the External Examiner**

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The success in this project would not have been possible but for the timely help and guidance rendered by many people. Our wish to express my sincere thanks to all those who has assisted us in one way or the other for the completion of my project.

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**ABSTRACT**

The project titled **" CodeCrafter "** explores the fine-tuning and deployment of a large language model (LLM) using the Cohere platform, demonstrating a practical application of Artificial Intelligence and Machine Learning (AIML) in software development and user interaction. Our primary objective was to build a custom intelligent system that could generate relevant and context-aware responses based on specific inputs defined in a custom dataset.

To achieve this, we created a structured dataset consisting of input-output pairs—typically prompts and their expected responses. This dataset was directly uploaded to the Cohere website, which offers a user-friendly interface for model fine-tuning. Without the need to write any model training code, we selected a base model such as Cohere's "command" model and initiated the fine-tuning process. After completion, Cohere provided a unique model identifier that allowed us to access our customized model via their API.

Post fine-tuning, we integrated this model into a full-stack application. The frontend was built using frameworks like React or Flutter, while the backend—developed in technologies such as Flask or Node.js—was responsible for API communication with the Cohere platform. The application allows users to interact with the fine-tuned model by submitting prompts; in return, they receive intelligent responses tailored to the training data. This seamless interaction between the user and the AI model highlights the power of LLMs when customized for specific use cases.

Furthermore, we extended the project by performing data visualization on a portion of the dataset. This visualization provided a deeper understanding of the data's distribution, trends, and quality, and helped evaluate the model’s expected behavior. Through this project, we not only demonstrated how LLMs can be fine-tuned and integrated into real-world applications with ease but also emphasized the importance of data quality and visualization in building effective AI systems.

**INTRODUCTION**

In recent years, the advancement of Artificial Intelligence and Machine Learning (AIML) has revolutionized the way we interact with software systems. Large Language Models (LLMs) are at the forefront of this transformation, enabling machines to understand, generate, and respond to human language with remarkable accuracy. Our project, titled **“CodeCrafter”**, is a practical implementation of this concept, where we have successfully fine-tuned a pre-trained LLM using a custom dataset and integrated it into a functional application.

The primary objective of this project is to create a domain-specific AI system capable of generating responses tailored to user-defined inputs. By leveraging Cohere's LLM platform, we fine-tuned a base model with a dataset consisting of input-output pairs, making the model more relevant to our use case. This was achieved without the need for extensive coding, thanks to the simplified interface provided by Cohere.

Once fine-tuning was complete, we accessed the customized model through an API and embedded it into our application. The system comprises both frontend and backend components, ensuring a seamless user experience. The frontend captures user queries, while the backend processes these inputs, communicates with the Cohere API, and returns the model's response.

Additionally, we explored data visualization techniques to better understand the dataset used for training. This helped us gain insights into data trends, quality, and model behavior.

This documentation outlines the process, methodology, and results of our project. It highlights the real-world applicability of LLMs and demonstrates how AIML technologies can be utilized to build intelligent, responsive applications with minimal complexity.

**LITRATURE SURVEY**

The concept of fine-tuning Large Language Models (LLMs) has gained significant momentum in recent years, particularly with the rise of platforms such as OpenAI, Cohere, Hugging Face, and others that provide infrastructure for model customization. Numerous research studies and industry applications have demonstrated the value of tailoring pre-trained models to suit specific tasks, domains, or datasets. This section reviews the key literature and tools relevant to our project, providing a foundation for understanding the methods and technologies employed.

**1. Large Language Models (LLMs):**  
LLMs such as GPT, BERT, and Cohere’s Command model have demonstrated remarkable capabilities in understanding and generating natural language. These models are pre-trained on massive datasets and can perform a variety of language tasks including summarization, question answering, translation, and content generation. However, their generalized nature often requires fine-tuning to adapt them to specific domains.

**2. Fine-Tuning Techniques:**  
Fine-tuning involves training a pre-existing model further on a specific dataset to adapt it to a more targeted use case. Traditional methods require writing training scripts and setting up computational infrastructure, but recent advancements in platforms like Cohere have simplified this process. Studies have shown that fine-tuning even with small datasets can yield high-quality, domain-specific results, especially when the base model is already well-trained.

**3. Cohere Platform:**  
Cohere is an AI company that offers user-friendly APIs for NLP tasks and allows developers to fine-tune models via a no-code interface. Literature on Cohere’s API indicates that it is optimized for ease of use, speed, and accuracy. Its base models (like command-xlarge) are designed for general-purpose tasks but can be adapted through fine-tuning to perform specialized functions more effectively.

**4. API Integration in Applications:**  
Integrating AI models into applications through APIs is a common practice in modern development. This allows developers to build smart applications without dealing with the complexities of deploying and managing models themselves. Research highlights the importance of building robust backend systems that securely handle communication with model APIs and serve the results efficiently to the frontend.

**5. Importance of Dataset Design and Visualization:**  
Numerous studies have emphasized the role of high-quality datasets in training effective AI models. Proper formatting, consistency in input-output pairs, and relevance to the intended use case significantly impact the performance of fine-tuned models. Data visualization helps in understanding dataset characteristics, spotting anomalies, and ensuring quality before training begins.

**CLIENT MEETINGS**

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Throughout the development of the CodeCrafter project, regular meetings were conducted with the client to ensure alignment with their expectations and to gather valuable feedback at each stage. These meetings played a crucial role in shaping the direction of the project and ensuring successful implementation.

**HARDWARE AND SOFTWARE**

|  |  |
| --- | --- |
| **Software/Tool** | **Purpose** |
| **Cohere Platform** | **Fine-tuning LLM and API-based model access** |
| **React / Flutter** | **Frontend development for user interaction** |
| **Flask / Node.js** | **Backend development and API integration** |
| **Postman** | **API testing and debugging** |
| **Visual Studio Code** | **Code editing and version control integration** |
| **Git & GitHub** | **Version control and collaboration** |
| **Python / JavaScript** | **Backend logic and server communication scripting** |
| **Google Chrome / Firefox** | **Application testing and debugging in the browser** |
| **Data Visualization Tools** | **For graphically representing parts of the dataset (e.g., Matplotlib, Chart.js)** |

software resources ensured a smooth development workflow, efficient testing, and seamless integration of the fine-tuned model with the application frontend and backend.

**IMPLEMENTATION**

The development of the **CodeCrafter** project followed a systematic, step-by-step process to ensure efficient integration of a fine-tuned LLM into a responsive application. Below is a detailed explanation of the implementation stages:

**Step 1: Dataset Preparation**

* A custom dataset was created in the form of input-output pairs (prompts and expected responses).
* The data was structured in a format compatible with Cohere's fine-tuning requirements (typically JSONL).
* Quality checks were done to ensure consistency, clarity, and relevance of the data.

**Step 2: Model Selection and Fine-Tuning on Cohere**

* Logged into the [Cohere](https://cohere.com) platform and selected the **Command** base model.
* Uploaded the prepared dataset directly through Cohere's user-friendly interface.
* Started the fine-tuning process without writing any model training code.
* After completion, Cohere generated a unique model ID which could be used for API access.

**Step 3: Backend Development**

* Created a backend using **Flask** (or **Node.js**) to handle communication between the frontend and the Cohere model.
* Integrated the Cohere API using secure API keys.
* Developed endpoints that receive user input, send it to the fine-tuned model, and return the generated response to the frontend.

**Step 4: Frontend Development**

* Designed a clean and responsive user interface using **React** (or **Flutter**).
* Developed input fields for user prompts and an area to display model responses.
* Implemented form submission and connected it to the backend using REST API calls (e.g., axios or fetch).

**Step 5: API Communication**

* Ensured proper connection between frontend and backend.
* When a user enters a prompt, the frontend sends the data to the backend.
* The backend forwards this input to the Cohere API, fetches the response, and sends it back to the frontend for display.

**Step 6: Data Visualization**

* Selected a portion of the dataset for visualization purposes.
* Used tools such as **Matplotlib** (Python) or **Chart.js** (JavaScript) to generate visual insights like:
  + Prompt frequency
  + Word usage
  + Dataset length distribution
* This helped in evaluating dataset quality and understanding model behavior.

**Step 7: Testing and Debugging**

* Used **Postman** to test API endpoints and ensure proper request-response cycles.
* Debugged frontend and backend integration issues.
* Verified the quality of model responses in comparison to expected outputs.

This step-by-step implementation provided a clear roadmap for building an intelligent, LLM-driven application with strong user interaction and data-driven insights.

**EXPERIMENTATION AND CODE**

The experimentation phase in the **CodeCrafter** project was crucial in validating the model's performance, testing the API integration, and ensuring a smooth end-to-end workflow from data to response. This section provides an overview of the coding process, experimentation strategies, and insights gained through iterative testing.

**1. Dataset Formatting and Testing**

* The dataset was structured in JSONL format, containing pairs of prompt and completion fields.
* Before uploading, we tested a few prompt-response pairs manually using the Cohere playground to check response quality.
* This helped in refining the tone, clarity, and structure of prompts.

**2. Fine-Tuning Workflow on Cohere**

* After uploading the dataset, we selected the **Command** base model and initiated the fine-tuning job.
* The model training process was monitored on the Cohere dashboard.
* Once fine-tuning was completed, we received a unique model endpoint ID (e.g., command-nightly:custom-model-codecrafter-v1).

**2. Backend integration**

code (Python with Flask):

from flask import Flask, request, jsonify

from flask\_cors import CORS

import json

import random

import time

import cohere

app = Flask(\_\_name\_\_)

CORS(app)

# Initialize Cohere client with your API key

co = cohere.Client("Api key ")

# Keep the mock code samples as fallback

MOCK\_CODE\_SAMPLES = {

    "python": [

        "def hello\_world():\n    print('Hello, world!')\n\nhello\_world()",

        "import random\n\ndef roll\_dice():\n    return random.randint(1, 6)\n\nresult = roll\_dice()\nprint(f'You rolled a {result}')",

        "class Calculator:\n    def add(self, a, b):\n        return a + b\n\n    def subtract(self, a, b):\n        return a - b\n\ncalc = Calculator()\nprint(calc.add(5, 3))"

    ],

    "javascript": [

        "function helloWorld() {\n  console.log('Hello, world!');\n}\n\nhelloWorld();",

        "const array = [1, 2, 3, 4, 5];\nconst doubled = array.map(num => num \* 2);\nconsole.log(doubled);",

        "class Person {\n  constructor(name, age) {\n    this.name = name;\n    this.age = age;\n  }\n\n  greet() {\n    return `Hello, my name is ${this.name}`;\n  }\n}\n\nconst person = new Person('John', 30);\nconsole.log(person.greet());"

    ],

    "html": [

        "<!DOCTYPE html>\n<html>\n<head>\n  <title>My Page</title>\n</head>\n<body>\n  <h1>Hello, World!</h1>\n  <p>This is a simple HTML page.</p>\n</body>\n</html>",

        "<!DOCTYPE html>\n<html>\n<head>\n  <title>Form Example</title>\n</head>\n<body>\n  <form>\n    <label for=\"name\">Name:</label>\n    <input type=\"text\" id=\"name\" name=\"name\"><br>\n    <label for=\"email\">Email:</label>\n    <input type=\"email\" id=\"email\" name=\"email\"><br>\n    <input type=\"submit\" value=\"Submit\">\n  </form>\n</body>\n</html>"

    ],

    "css": [

        "body {\n  font-family: Arial, sans-serif;\n  background-color: #f0f0f0;\n  margin: 0;\n  padding: 20px;\n}\n\nh1 {\n  color: #333;\n  text-align: center;\n}",

        ".container {\n  max-width: 1200px;\n  margin: 0 auto;\n  padding: 15px;\n  display: flex;\n  flex-wrap: wrap;\n}\n\n.card {\n  width: 300px;\n  border: 1px solid #ddd;\n  border-radius: 8px;\n  padding: 15px;\n  margin: 10px;\n  box-shadow: 0 4px 8px rgba(0,0,0,0.1);\n}"

    ],

    "react": [

        "function App() {\n  return (\n    <div>\n      <h1>Hello React!</h1>\n    </div>\n  );\n}\n\nexport default App;",

    ],

    "java": [

        "public class HelloWorld {\n    public static void main(String[] args) {\n        System.out.println(\"Hello, World!\");\n    }\n}"

    ],

    "c": [

        "#include <stdio.h>\n\nint main() {\n    printf(\"Hello, World!\\n\");\n    return 0;\n}"

    ],

    "cpp": [

        "#include <iostream>\n\nint main() {\n    std::cout << \"Hello, World!\" << std::endl;\n    return 0;\n}"

    ],

    "csharp": [

        "using System;\n\nclass Program {\n    static void Main() {\n        Console.WriteLine(\"Hello, World!\");\n    }\n}"

    ],

    "go": [

        "package main\n\nimport \"fmt\"\n\nfunc main() {\n    fmt.Println(\"Hello, World!\")\n}"

    ],

    "ruby": [

        "puts \"Hello, World!\""

    ],

    "php": [

        "<?php\necho \"Hello, World!\";\n?>"

    ],

    "swift": [

        "print(\"Hello, World!\")"

    ]

}

@app.route('/api/generate', methods=['POST'])

def generate\_code():

    data = request.json

    prompt = data.get('prompt', '')

    language = data.get('language', 'python')

    try:

        # Create a prompt that specifies what we want from Cohere

        cohere\_prompt = f"Generate {language} code for the following request: {prompt}\n\nOnly return the code, no explanations."

        # Call the Cohere API to generate code

        response = co.generate(

            prompt=cohere\_prompt,

            max\_tokens=500,

            temperature=0.7,

            k=0,

            stop\_sequences=[],

            return\_likelihoods='NONE'

        )

        # Extract the generated code from Cohere's response

        generated\_code = response.generations[0].text

        # Clean up the code (remove any markdown code fences if present)

        if generated\_code.startswith("```"):

            lang\_line\_end = generated\_code.find("\n")

            generated\_code = generated\_code[lang\_line\_end:].strip()

        if generated\_code.endswith("```"):

            generated\_code = generated\_code[:-3].strip()

        return jsonify({

            'code': generated\_code,

            'language': language

        })

    except Exception as e:

        # Log the error

        print(f"Error with Cohere API: {str(e)}")

        # Improved fallback handling

        if language in MOCK\_CODE\_SAMPLES:

            code = random.choice(MOCK\_CODE\_SAMPLES[language])

        else:

            # Default to Python if language not found

            code = random.choice(MOCK\_CODE\_SAMPLES["python"])

            language = "python"

        return jsonify({

            'code': code,

            'language': language

        })

@app.route('/api/languages', methods=['GET'])

def get\_languages():

    languages = [

        {"id": "python", "name": "Python"},

        {"id": "javascript", "name": "JavaScript"},

        {"id": "html", "name": "HTML"},

        {"id": "css", "name": "CSS"},

        {"id": "react", "name": "React"},

        {"id": "java", "name": "Java"},

        {"id": "c", "name": "C"},

        {"id": "cpp", "name": "C++"},

        {"id": "csharp", "name": "C#"},

        {"id": "go", "name": "Go"},

        {"id": "ruby", "name": "Ruby"},

        {"id": "php", "name": "PHP"},

        {"id": "swift", "name": "Swift"}

    ]

    return jsonify(languages)

if \_\_name\_\_ == '\_\_main\_\_':

    app.run(debug=True)

**4. Frontend Code:**

import React, { useRef } from 'react';

import { Button } from "@/components/ui/button";

import { Copy, Check } from "lucide-react";

import { toast } from "sonner";

interface CodeEditorProps {

  code: string;

  language: string;

  isLoading: boolean;

}

const CodeEditor: React.FC<CodeEditorProps> = ({ code, language, isLoading }) => {

  const [copied, setCopied] = React.useState(false);

  const codeRef = useRef<HTMLPreElement>(null);

  const copyToClipboard = () => {

    if (code) {

      navigator.clipboard.writeText(code);

      setCopied(true);

      toast.success("Code copied to clipboard!");

      setTimeout(() => {

        setCopied(false);

      }, 2000);

    }

  };

  // Add syntax highlighting class based on language

  const getLanguageClass = () => {

    return `language-${language || 'plaintext'}`;

  };

  return (

    <div className="bg-gray-900 rounded-lg shadow-lg overflow-hidden w-full">

      <div className="flex justify-between items-center px-4 py-2 bg-gray-800 border-b border-gray-700">

        <div className="flex space-x-2">

          <div className="w-3 h-3 rounded-full bg-red-500"></div>

          <div className="w-3 h-3 rounded-full bg-yellow-500"></div>

          <div className="w-3 h-3 rounded-full bg-green-500"></div>

        </div>

        <div className="text-gray-400 text-xs font-mono">

          {language || 'plaintext'}

        </div>

        <Button

          variant="ghost"

          size="sm"

          className="text-gray-400 hover:text-white hover:bg-gray-700"

          onClick={copyToClipboard}

          disabled={isLoading || !code}

        >

          {copied ? <Check size={16} /> : <Copy size={16} />}

        </Button>

      </div>

      <div className="p-4 overflow-auto max-h-[500px]">

        {isLoading ? (

          <div className="flex items-center justify-center h-20">

            <div className="animate-spin rounded-full h-8 w-8 border-t-2 border-b-2 border-blue-500"></div>

          </div>

        ) : code ? (

          <pre ref={codeRef} className={`text-gray-300 font-mono text-sm ${getLanguageClass()}`}>

            <code>{code}</code>

          </pre>

        ) : (

          <div className="text-gray-500 flex items-center justify-center h-20">

            Enter a prompt to generate code

          </div>

        )}

      </div>

    </div>

  );

};

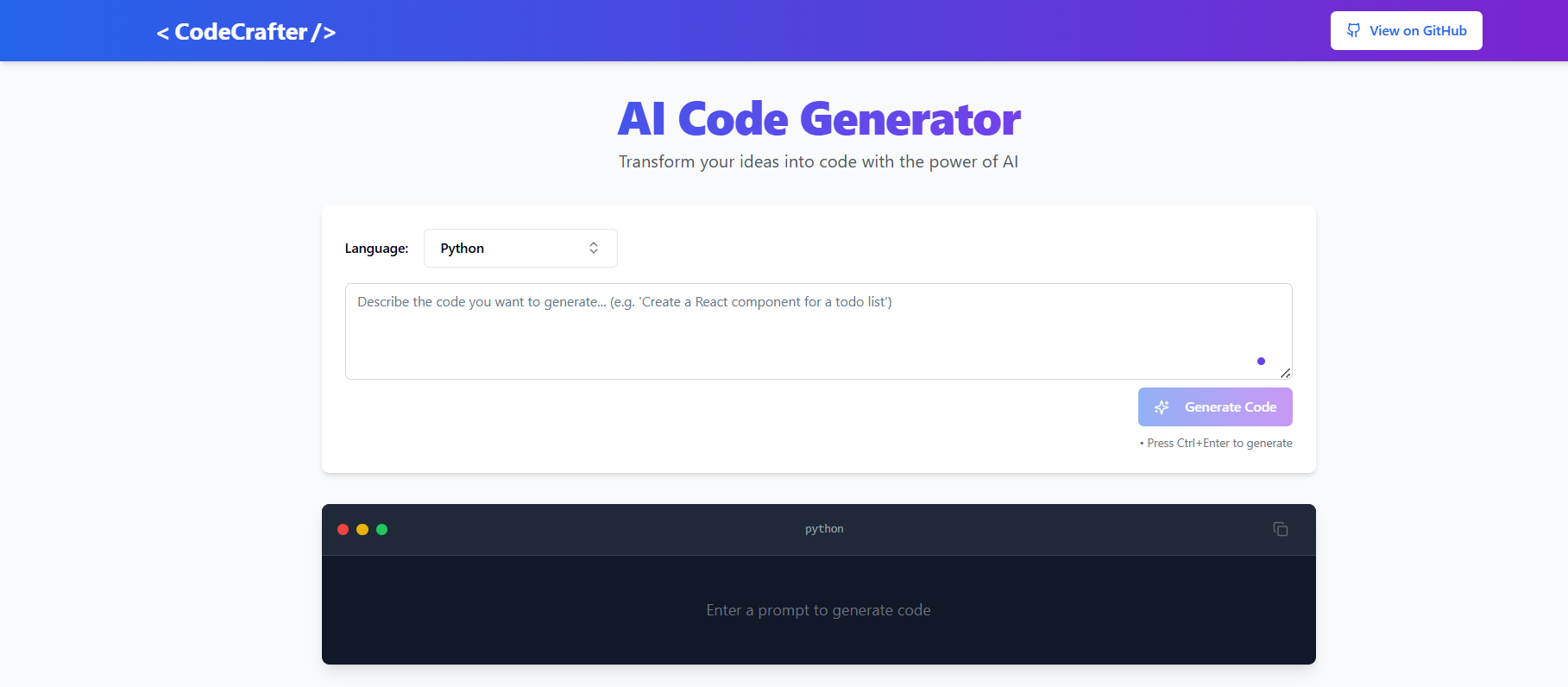
export default CodeEditor;

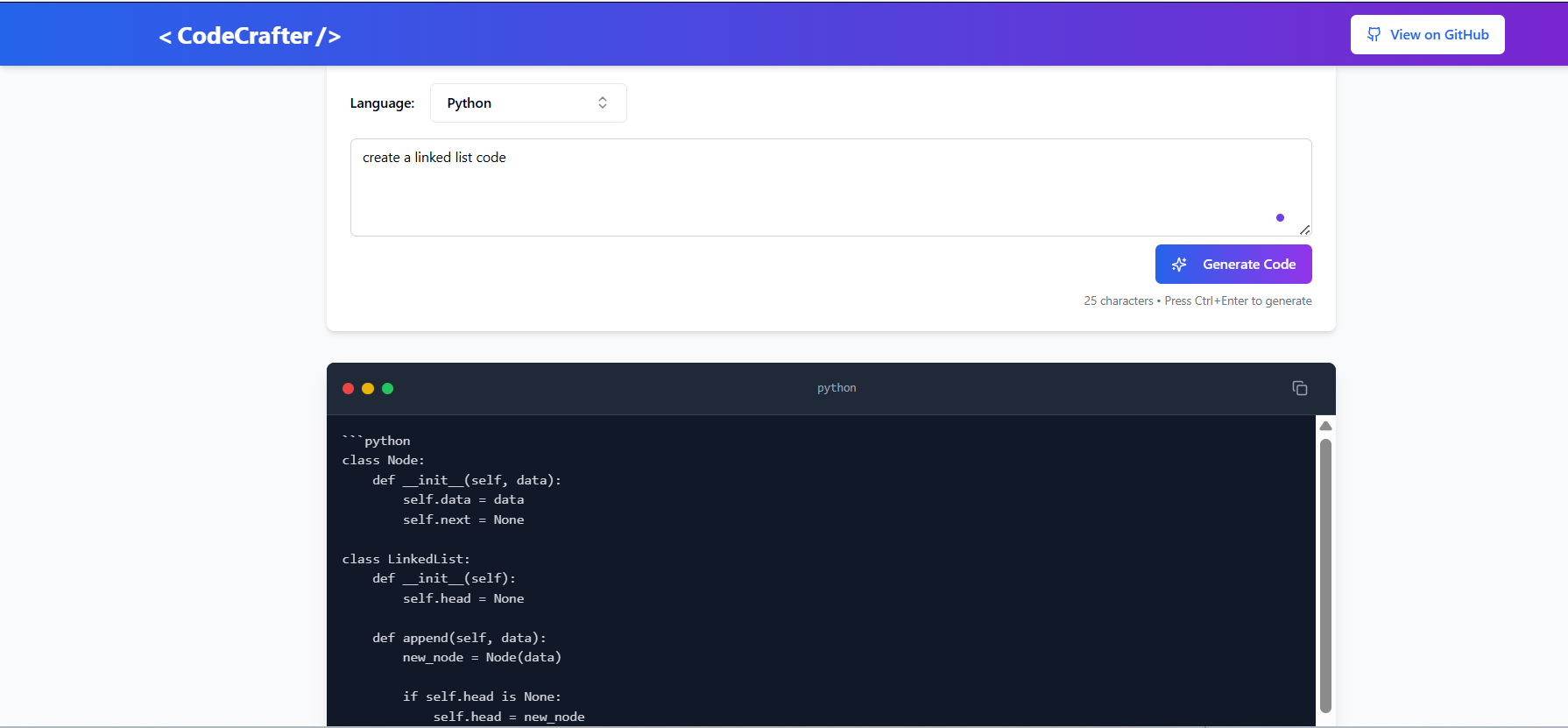
**5. Experimentation Results**

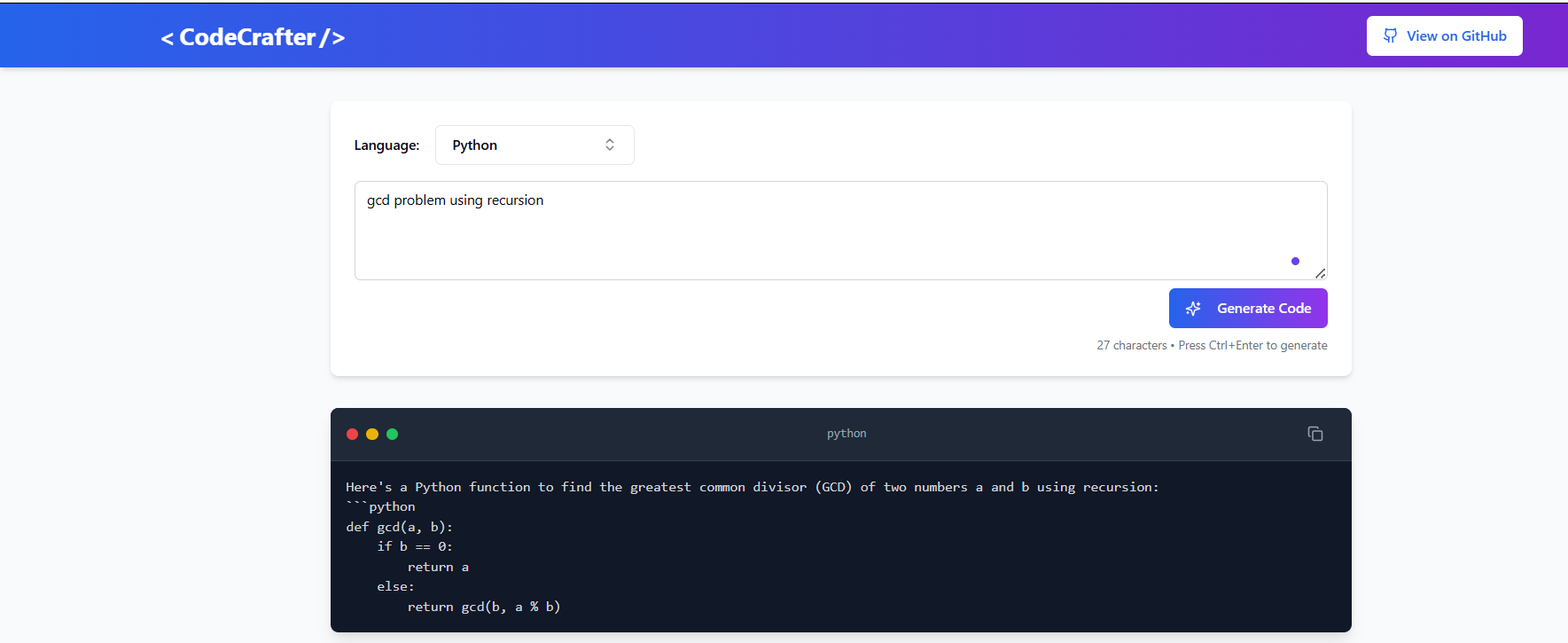
* **Initial Testing:** The model responded well to most prompts, but minor fine-tuning adjustments were needed.
* **Prompt Engineering:** Experimented with different prompt phrasings to improve context understanding and output quality.
* **Latency Testing:** Measured response time from frontend to Cohere and back; API responses were generally fast and reliable.
* **Error Handling:** Implemented backend try-catch logic to gracefully handle API timeouts and empty inputs.

Through this phase, we iteratively improved model behavior, verified application stability, and ensured that CodeCrafter delivered accurate, context-aware responses aligned with our custom dataset.

**Results**

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**CONCLUSION**

The **CodeCrafter** project successfully demonstrates how modern AI tools and platforms like Cohere can be leveraged to build intelligent, responsive applications with minimal infrastructure complexity. By fine-tuning a Large Language Model (LLM) using a custom dataset and integrating it into a full-stack application, we were able to create a system capable of understanding and generating contextually relevant responses.

Throughout the development process, we gained hands-on experience in dataset preparation, prompt design, model fine-tuning, API integration, and user interface development. The project also highlighted the importance of experimentation, visualization, and continuous iteration to improve model behavior and user satisfaction.

One of the key achievements of CodeCrafter was the successful end-to-end integration of the fine-tuned LLM—from backend logic to real-time user interaction on the frontend. Additionally, the use of data visualization helped us understand the structure and distribution of our training data, allowing for better evaluation and refinement.

In conclusion, CodeCrafter serves as a practical example of how AIML technologies can be applied in real-world scenarios. It provides a solid foundation for further enhancements such as multi-language support, advanced NLP features, or scaling with larger datasets. This project not only deepened our understanding of AI systems but also demonstrated the power of collaborative development and innovation in the field of intelligent applications.