

Analysis ChatGPT Potential: Transforming Software Development with AI Chat Bots

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Abstract—Artificial intelligence (AI) is a technology that is constantly evolving and is being applied more frequently in many facets of society, including product and service development. Chatbots, which are computer programs that can connect with people through chat or voice apps, are one sort of AI that is evolving quickly. However, there is still much debate among scientists and professionals about whether AI advancements like ChatGPT can help software engineers with their daily tasks or even replace the work of software engineers. So, on this occasion, we conduct research on whether AI (artificial intelligence) is capable of helping software engineers and how far AI can assist software engineers. In this study, we aim to evaluate the effectiveness of ChatGPT as an AI tool for code retrieval and its potential to help or replace software engineers. Our research methodology involves using ChatGPT to refactor provided code and make a simple application from scratch. The results of this research show that AI chatbot models like ChatGPT cannot replace software developers 100

Index Terms—Artificial Intelligent, Software Development, Chat Bot

I. INTRODUCTION

Software development is difficult and requires a high level of ability and knowledge. Yet, new potential to increase the effectiveness of software development has emerged as a result of recent developments in artificial intelligence. The use of ChatGPT, a sophisticated language model trained on the GPT-3.5 architecture, is one such development. With encouraging outcomes, ChatGPT has been used to produce code for a number of software applications [1]. In this essay, we investigate the use of ChatGPT to generate code for software applications and assess the usability and quality of the produced code.

ChatGPT is a potent tool that can produce code and natural language writing. ChatGPT has been trained in a variety of programming languages and can learn from a great deal of data. When creating code with ChatGPT, input text is given

to the model, which subsequently creates code depending on the input [2]. Human software engineers can then polish and enhance the generated code. The speed and effectiveness of software development can both be increased by this technique.

ChatGPT-produced software's usefulness and quality The findings have been positive, with the program doing well in several tasks, including natural language processing, image recognition, and game development [2]. However, some people said the software produced by ChatGPT still has certain limitations. In rare circumstances, the software may not operate as planned because of mistakes in the code. Also, code produced by ChatGPT could not be as effective as code authored by real software developers [2]. While some work has been done to better understand the interplay between Software Engineering and AI, we still lack methodologies for classifying ways of implementing AI in software systems as well as analyzing and understanding the hazards that this creates. Only by doing so will we be able to develop tools and solutions to assist reduce them [4]. This experiment aims to provide an overview of AI's benefits and limitations in software development by examining current literature and suggesting topics for further investigation [3]–[6].

Risk management is a vital aspect of software development; in this situation, AI has assisted developers in analyzing every possible risk and devising solutions to reduce it [7]. Moreover, in software testing, AI-driven techniques have the potential to revolutionize quality assurance work, speed up time to market, and enable businesses to create more complex software [8]–[10]. AI has been employed in various software development sectors, including project management, design, testing, and requirements engineering, with the potential to enhance software quality by automating repetitive tasks, identifying mistakes, and supporting decision-making [11].

AI's impact extends beyond traditional software development to industries such as e-commerce and IT telecom, where AI-powered chatbots have been shown to improve customer satisfaction and service efficiency [12]–[15]. In web-based software development, AI and machine learning can lead to higher quality and efficiency in applications [16], [17]. Despite the advantages, developing AI-based chatbots can be challenging, with IBM Watson being identified as the best method among widely used Natural Language Understanding (NLU) techniques [18].

AI has also been employed in software development effort estimation, with the FNN approach demonstrating higher accuracy in overcoming uncertainty and vagueness [19]. Furthermore, natural language processing (NLP) advancements, such as GPT-3, GPT-4, and ChatGPT, have generated interest in their potential applications in computer programming [20], [21]. ChatGPT has demonstrated promising results in producing code snippets [2], [22], and [23]. ChatGPT can also help programmers fix their bugs efficiently [1].

AI, such as ChatGPT, offers numerous advantages in software development, but it is essential to consider the drawbacks, limitations, ethical, and transparency issues surrounding this technology [9], [25], [26]. Even with that understanding, ChatGPT could pass Algorithm and Data Structure while participating in an undergraduate computer science examination, which in other circumstance students might use it to cheat [24]. Furthermore, despite the fact that there are established rules known as the seven key requirements for trustworthy AI, many businesses do not follow them effectively [27]. Therefore, in this research, we have experiments that determine whether ChatGPT can help or do programmer jobs in terms of software engineering. This paper is arranged as follows: First, in Section 2, we discuss the methodology of our experiments, such as how we conduct our experiments, prompting, or how we determine the results of our tests. In Section 3, we conducted the experiment that was discussed in the methodology section. Finally, in Section 4, we concluded our work with the experiment results and made future improvements for the next research.

II. METHODOLOGY

Through a series of tests, we asked the ChatGPT model to carry out various coding and software development-related activities as part of the study. The ChatGPT is available on <https://chat.openai.com/> and can be used and opened by all registered accounts. Our model is using the 3.5 ChatGPT version, so you can use it for testing the available code. We use simple prompting techniques for refactoring, bug fixing, and machine learning, like "refactor the below code with...", etc.

To evaluate the results of the experiments, after we prompt ChatGPT, we analyze the answers given by ChatGPT with the answers that have been created by our team and draw conclusions about whether the answers given by ChatGPT are in accordance with our answers. For the simple application

experiment, the program was directly tested, and our team provided a conclusion on the created program by ChatGPT.

You can get all the source code and implementation information in our GitHub repository: <https://github.com/TinTinWinata/chat-gpt-analysis>. The repository includes all of the tested's experiments, including refactoring code, machine learning, and simple applications, as well as the entire codebase, including the HTML and JavaScript files.

A. Refactor Code

Our team provided a piece of smelly code in C# that consisted of a self-encapsulation field and an inline temperature. You can see the explanation of smell code at Refactoring Guru (<https://refactoring.guru/>), and the code is available on our github repository. The piece of smell code that must be refactored is sent to the ChatGPT model by using simple prompt techniques. The code needs to be refactored, and the ChatGPT model requested that a new and improved version of the code be submitted. The result of the refactored code gets analyzed with various scores, like effectiveness and correctness of code.

B. Simple Application

The ChatGPT model was asked to design a tic-tac-toe game in order to build a simple application. The ChatGPT model is required to provide the JavaScript programming language code required to develop the application and ensure its proper operation. Furthermore, we challenged ChatGPT to add bots that can fight humans, as well as to make the bot smart enough to beat humans. The generated code is then tested by playing the game and determining who wins.

```
can you make a tic tac toe game in
javascript that comes with human vs
bot game, where the human cannot win
against the bot
```

Script. 1. Simple Application Prompt

From the figure above, the prompt is a clear and concise question asking for the creation of a specific application—a tic-tac-toe game in JavaScript. The prompt further specifies that the game should include a human vs. bot mode where the human player cannot win against the bot player.

C. Machine Learning

The results of this machine learning testing are to create a machine learning code to predict whether the user has diabetes or not. This machine learning code prediction is provided by the Naïve Bayes approach to make the two types of classifications: diabetes classification and not diabetes classification.

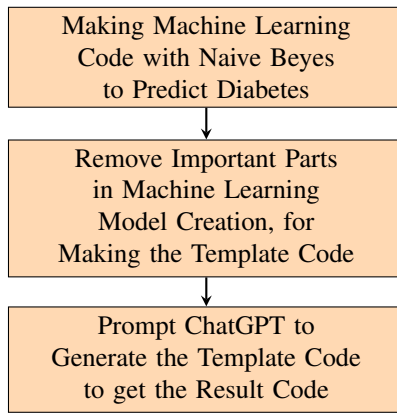


Fig. 1. Flowchart of the Machine Learning Methodology Process

First, we create a machine learning code to predict whether the user has diabetes or not. We're using a naive bayes approach and python programming language to make the machine learning code. The dataset that we used is diabetes data that you can find in Kaggle and our github repository. We also use an advanced library like sklearn, numpy, matplotlib, and pandas so that we can see the performance of the ChatGPT to using the provided library.

After we create the code, we discard the important modeling code and leave the rest of the code to the ChatGPT. When we discard important code, we give a sign to ChatGPT to recreate the code in a specific section. For a fair comparison, we didn't remove the load dataset code because the ChatGPT model didn't know the column and the value of the dataset.

```

# Naive Bayes

# Importing the libraries
from enum import Enum

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from matplotlib.colors import ListedColormap
from sklearn import metrics
from sklearn.metrics import accuracy_score,
confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler

class SmokingHistory(Enum):
    NOINFO = 'No Info'
    NEVER = 'never'
    CURRENT = 'current'
    FORMER = 'former'
    NOTCURRENT = 'not current'
    EVER = 'ever'

class Gender(Enum):
    MALE = 'Male'
    FEMALE = 'Female'

class NaiveBayes():

    def __init__(self, file_name, data):
        self.data = data
        self.sc = StandardScaler()
        self.load_dataset(file_name=file_name)
        self.split_dataset()
        self.feature_scaling()
  
```

```

self.training_dataset()
self.test_result()

def load_dataset(self, file_name):
    # Importing the dataset
    self.dataset = pd.read_csv(file_name)
    self.X = self.dataset.iloc[:, :-1].values
    self.y = self.dataset.iloc[:, -1].values
    for item in self.X:

        # Changing Gender
        if item[0] == Gender.FEMALE.value:
            item[0] = 0
        else:
            item[0] = 1

        # Changing Smoking History
        if item[4] == SmokingHistory.NOINFO.value:
            item[4] = 0
        elif item[4] == SmokingHistory.NEVER.value:
            item[4] = 1
        elif item[4] == SmokingHistory.FORMER.value:
            item[4] = 2
        elif item[4] == SmokingHistory.CURRENT.value:
            item[4] = 3
        elif item[4] == SmokingHistory.NOTCURRENT.value:
            item[4] = 4
        elif item[4] == SmokingHistory.EVER.value:
            item[4] = 5
        else:
            print(f'Unknown Value : {item[4]}')

def split_dataset(self):
    # TODO: Split the self.X & self.y (dataset) into
    # Training data and Test data
    print('generate this code')

def feature_scaling(self):
    # TODO: Make a Feature Scaling for the training
    print('generate this code')

def training_dataset(self):
    # TODO: Training the train data with Naive Bayes
    # Algorithm to make the model
    print('generate this code')

def test_result(self):
    # TODO: Print the Confusion Matrix and make a
    # prediction accurate percentage based on the
    # model on training_dataset method
    print('generate this code')

def predict_data(self):
    # TODO: Predict the self.data input from the user
    # based on the created model
    print('generate this code')

def draw_cm_matrix(self):
    cm_display = metrics.ConfusionMatrixDisplay(
        confusion_matrix=self.cm, display_labels=[False, True])
    cm_display.plot()
    plt.show()

gender = 1
age = 19
hypertension = 0
heart_disease = 0
smoking_history = 0
bmi = 24.2
HbA1c_level = 5
blood_glucose_level = 130

data = [gender, age, hypertension, heart_disease,
        smoking_history, bmi, HbA1c_level,
        blood_glucose_level]

model = NaiveBayes(file_name='diabetes_data.csv', data=data)
  
```

Script. 2. Template Code to be Filled by ChatGPT Model

The ChatGPT model built the machine learning model and generated the forecast of diabetes. The goal of this methodology is to make a comparison between our first code, which was made by our team, and the result of the generated code by ChatGPT. Then, we analyzed the result of the prediction for the correct percentage using a confusion matrix and compared the value result with our team code.

```
gender = 1
age = 19
hypertension = 0
heart_disease = 0
smoking_history = 0
bmi = 24.2
HbA1c_level = 5
blood_glucose_level = 130

You are not diabetes!
Accuracy score: 0.90488
```

Script. 3. Given Input & Our Diabetes Result

III. EXPERIMENTS & RESULTS

We outline the experiments conducted to address our research questions in this experiment and result section. In Section A, we look at how ChatGPT may assist programmers with code refactoring. We examine ChatGPT's capabilities for basic application generation and machine learning prediction in Sections B and C. Refactor Code.

A. Refactor Code

Leveraging the power of artificial intelligence, we conducted experiments using C. Based on the experiment results, ChatGPT provides best practices for code refactoring, including separating logic into multiple functions, avoiding code duplication, and more.

```
public class Account
{
    private int money;
    public Account(int money)
    {
        this.money = money;
    }
    public int withdraw(int amount)
    {
        int temp = this.money - amount;
        return temp;
    }
}
```

Script. 4. Unfactored Code

```
public class Account
{
    private int money;

    public Account(int money)
    {
        this.money = money;
    }

    public int getMoney()
    {
        return money;
    }

    public void withdraw(int amount)
    {
        money -= amount;
    }
}
```

// ChatGPT Explanation:

```
// We encapsulated the money field by making it private.
// This ensures that it can only be accessed through the
// getter method.
// We added a getter method getMoney() to provide read-only
// access to the money field. This allows other classes
// to retrieve the current balance of the account.
// In the withdraw method, we directly subtract the amount
// from the money field. This eliminates the need for the
// temp variable and simplifies the code.
// By applying these changes, we have removed the Self
// Encapsulation Field smell and improved the code by
// adhering to encapsulation principles.
```

Script. 5. Refactored Code

The figure above shows ChatGPT improved the structure, readability, and adherence to best practices in application development. As we can see from language modeling, ChatGPT can know where's the smell code and implement a refactored code. They remove the self-encapsulation field smell code and implement getter and setter in the code. But for the inline temperature smell in the previous code, the ChatGPT removed the code and changed it to only deduct the current money. This will be a problem because initially we want to get our money, but instead, the money is not received and produces a void return.

The results generated by ChatGPT also align with universal principles and standards in application development. The resulting code is well-structured, easier to test, and maintainable. Overall, ChatGPT can greatly assist in the software development process by addressing smell code and enhancing the overall code quality of applications. However, the code created by ChatGPT may contain mistakes and misconceptions. As developers, it is critical that we comprehend and properly evaluate the code generated by ChatGPT.

B. Simple Application

The analysis focuses on how well ChatGPT generates code that can execute properly and adhere to standards. We put it to the test by giving ChatGPT a prompt to create a game of tic-tac-toe that uses HTML, CSS, and JavaScript programming languages. As a result, when we play the game of tic-tac-toe, the ChatGPT model is able to accomplish this and pass the test.

We also sent the prompt to ChatGPT to enable human vs. bot play in the game. We also asked it to make the bot as intelligent as possible so that it could outplay people at the game of tic-tac-toe. It turns out ChatGPT uses the mini-max algorithm to decide the best moves in order to guarantee that the bot always wins or at least manages to achieve a draw when playing the tic-tac-toe game.

This experiment demonstrated ChatGPT's flexibility in implementing complex algorithms in addition to producing functional code. ChatGPT successfully developed a fully playable tic-tac-toe game with a clever bot opponent by combining its knowledge of game theory and programming languages. This highlights the model's potential even more as a useful tool for creating interactive programs and games.

```
function minimax(board, depth, isMaximizing) {
  if (checkWin("X")) return -1;
  if (checkWin("O")) return 1;
  if (isBoardFull()) return 0;

  if (isMaximizing) {
    let bestScore = -Infinity;
    for (let i = 0; i < 9; i++) {
      if (board[i] === "") {
        board[i] = "O";
        let score = minimax(board, depth + 1, false);
        board[i] = "";
        bestScore = Math.max(score, bestScore);
      }
    }
    return bestScore;
  } else {
    let bestScore = Infinity;
    for (let i = 0; i < 9; i++) {
      if (board[i] === "") {
        board[i] = "X";
        let score = minimax(board, depth + 1, true);
        board[i] = "";
        bestScore = Math.min(score, bestScore);
      }
    }
    return bestScore;
  }
}
```

Script. 6. Mini-Max Algorithm Made by ChatGPT

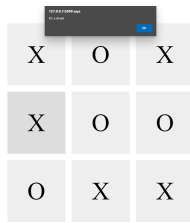


Fig. 2. Bot draw against human.

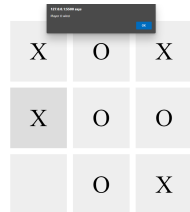


Fig. 3. Bot won against human.

C. Machine Learning

Our machine learning research centered on using ChatGPT to generate code that could determine whether user input suggests diabetes. According to the methodology section, we used machine learning code templates that were already created to be filled in by the ChatGPT model.

```
def split_dataset(self):
  # TODO: Split the self.X & self.y (dataset) into
  # Training data and Test data
  self.X_train, self.X_test, self.y_train, self.
  y_test = train_test_split(
    self.X, self.y, test_size=0.25, random_state=0)

def feature_scaling(self):
  # TODO: Make a Feature Scaling for the training
  self.X_train = self.sc.fit_transform(self.X_train)
```

```
def training_dataset(self):
  # TODO: Training the train data with Naive Bayes
  # Algorithm to make the model
  self.classifier = GaussianNB()
  self.classifier.fit(self.X_train, self.y_train)

def test_result(self):
  # TODO: Print the Confusion Matrix and make a
  # prediction accurate percentage based on the
  # model on training_dataset method
  self.X_test = self.sc.transform(self.X_test)
  y_pred = self.classifier.predict(self.X_test)
  self.cm = confusion_matrix(self.y_test, y_pred)
  accuracy = accuracy_score(self.y_test, y_pred)
  print("Confusion Matrix:")
  print(self.cm)
  print("Prediction Accuracy:", accuracy)

def predict_data(self):
  # TODO: Predict the self.data input from the user
  # based on the created model
  data_scaled = self.sc.transform([self.data])
  prediction = self.classifier.predict(data_scaled)
  if prediction[0] == 1:
    print("The user is predicted to have diabetes.")
  else:
    print("The user is predicted to not have
    diabetes.")
```

Script. 7. Model Code that Filled from Template by ChatGPT

```
gender = 1
age = 19
hypertension = 0
heart_disease = 0
smoking_history = 0
bmi = 24.2
HbA1c_level = 5
blood_glucose_level = 130

Prediction Accuracy: 0.90488
The user is predicted to not have diabetes.
```

Script. 8. Given Input & ChatGPT Diabetes Result

Based on the user's input, this code was used to determine how likely it was that they would get diabetes. We conclude that the code that is generated by ChatGPT has the same answer as the human code. The code also has a 90.49% accuracy percentage to predict whether the user has diabetes or not, the same percentage number that the human-created code also has.

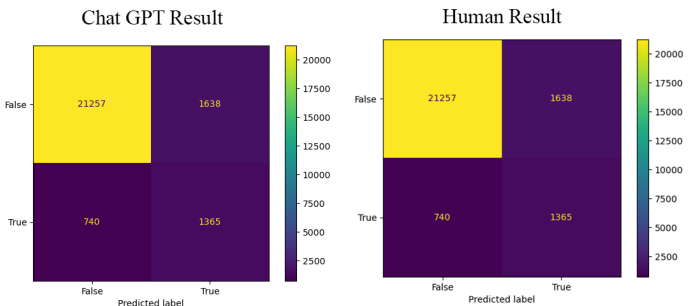


Fig. 4.

Figure above shows the confusion matrix for both human-coded and ChatGPT-generated solutions to give a visualization of performance. This visual depiction allows us to evaluate

the true positives, true negatives, false positives, and false negatives. By comparing the confusion matrices, ChatGPT performs similarly to human code in terms of accuracy.

Overall, the machine learning tests showed how well ChatGPT generates code for machine learning tasks, particularly for determining whether or not a person has diabetes. These findings demonstrate ChatGPT's potential as a useful tool for tackling difficult machine learning challenges. ChatGPT's ability to create accurate code enables it to aid developers and academics in efficiently handling challenging machine learning problems.

IV. CONCLUSION

The trials demonstrated ChatGPT's potential as a useful tool in software development. Developers may use its language generating features to help with bug patches, code restructuring, machine learning jobs, and the creation of small apps. While the experiments demonstrated ChatGPT's promise, it is crucial to recognize its limits. In rare circumstances, the code produced may contain flaws or fail to behave as planned. Furthermore, the model's reliance on training data raises worries about possible biases or weaknesses in the resulting code.

In the future, ChatGPT has a challenge to make itself adaptable to the appropriate context. They may generate correct code but actually lack a deeper understanding of what is being asked or the core of the problem. This can lead to incorrect solutions, potential security vulnerabilities, or inefficient code.

Despite their own limitations, it is impossible to ignore ChatGPT's potential influence on software development ethics. The model's capacity as a helpful tool for developers is demonstrated by its capacity to generate code that complies with industry standards and carry out challenging programming tasks. ChatGPT cannot replace 100% software development but With further development and improvement, ChatGPT has the potential to enhance and streamline software development workflows, and allowing developers to work more efficiently and creatively.

The ChatGPT model already has a new version, namely ChatGPT 4, and it produces better results than ChatGPT 3.5. Because there's a limitation in our research, all the research above is using ChatGPT 3.5, and we cannot see the difference between those versions. For the purpose of future research, we suggest making a comparison between another model like ChatGPT 4 or Google Bard. So, future research will not only find the function of the ChatGPT model in software development, but also encourage finding the best model to suit up software engineers to do a daily programmer task by comparing all existing models.

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