Internship Report

Artificial Intelligence and Machine Learning

DLithe Consultancy Services Pvt. Ltd.

Internship Report

Trainee/Intern Name: Anagha Bhoopalam T R

Reg. no: 4PM22MC003

Period: 6 weeks

Job Assignment:

Organization: DLithe Consultancy Services Pvt. Ltd.

Supervisor's Name: Bhavana A S

Observations:

Submitted to

Signature of Training Supervisor

Date:

Signature of Co-ordinator

Date:

Letter of Transmittal

To,

Program Co-ordinator
DLithe Consultancy services
Bengaluru

Dear Sir,

I am writing to submit my report on AIML Internship. The training program was an invaluable learning experience, and I am grateful for the opportunity to participate.

The training program covered various aspects of AI and ML, including basic concepts, algorithms, programming languages, and practical applications. I gained a comprehensive understanding of the role of AI and ML in modern technology and industry, and also gained hands-on experience with AI and ML tools and platforms. The training highlighted the potential of AI and ML to revolutionize various fields, including healthcare, finance, and manufacturing.

The report includes a detailed overview of the training program, including the topics covered, the learning objectives, and the outcomes achieved. It also provides observations and insights into the potential benefits and challenges of implementing AI and ML solutions in different fields.

I believe that the knowledge and skills that I acquired during the training program will be valuable to our organization. AI and ML are rapidly becoming more ubiquitous in various industries, and the ability to work with AI and ML tools and platforms will be increasingly important for our organization's success.

I hope that the report provides useful insights into the benefits of on-job training and the potential of AI and ML.

Sincerely,

Name: Anagha Bhoopalam T R

Reg. no: 4PM22MC003

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Introduction

Artificial Intelligence and Machine Learning are two of the most popular and rapidly growing fields in computer science. They are transforming the way we live, work, and interact with technology. The purpose of this report is to provide an overview of my Internship Training experience on Artificial Intelligence and Machine Learning, and to describe the various concepts and techniques that I learned during the training.

Background

The Internship Training program on Artificial Intelligence and Machine Learning that I participated in was conducted by a technology company. The program was designed to provide a comprehensive overview of the latest advancements in the field of AI and ML, and to equip participants with the skills and knowledge required to build intelligent systems and applications.

The training program consisted of practical hands-on sessions. The lectures covered a wide range of topics, including the fundamentals of AI and ML, various techniques and algorithms used in machine learning, and the latest developments in deep learning and neural networks. The practical sessions involved working on various projects and implementing machine learning algorithms on real-world datasets.

Project Overview

The presented project is an intent classification chatbot designed for healthcare interactions. The model architecture is built upon LSTM (Long Short-Term Memory) networks, known for their ability to capture sequential dependencies in data. The project involves data preprocessing steps such as tokenization, padding, and label encoding. The LSTM model is trained on a dataset containing labeled intents, allowing it to learn to recognize the purpose behind user messages. The model's architecture includes an embedding layer for vectorizing input tokens, an LSTM layer for sequential learning, and a dense output layer for intent prediction. The training process involves compiling the model with appropriate settings, visualizing training history, and saving the trained model. The chatbot demonstrates its capability by

making predictions on new data, providing responses based on recognized intents. The project's adaptability to healthcare scenarios is emphasized, indicating its potential utility in handling health-related queries and understanding medical terminology.

Problem Statement

The problem statement for this project revolves around developing a health-focused chatbot with intent classification capabilities. The goal is to create an intelligent system capable of understanding and categorizing user queries or messages related to healthcare. The specific challenges include training the model to recognize diverse healthcare intents, handling medical terminology, and adapting to the nuances of health-related conversations. The project aims to improve the user experience in seeking information or assistance in the healthcare domain, ultimately contributing to more effective and user-friendly interactions in a chatbot.

Solution

Methodology

The objective of the project that is a health care chatbot was to offer accessible and reliable health information, support, and guidance to users. Through a user-friendly interface, the chat bot aims to empower individuals by providing information on symptoms, medical conditions, treatments, and healthy living practices. It seeks to promote early symptom recognition, encourage proactive health management, and enhance overall health literacy. The chat bot strives to be available 24/7, ensuring convenience for users to access assistance at any time.

Data Exploration:

Dataset Description:

Provide insights into the healthcare-specific dataset, emphasizing the importance of intent labels, user queries related to health concerns, and the relevance of the chatbot in the healthcare domain.

Intent Labeling:

Examine the distribution of health-related intent labels, highlighting the significance of accurately classifying user queries for proper healthcare assistance.

Comparative Algorithm Selection:

Considered Algorithms:

Some algorithm such as CRF(Conditional Fields), CNN(Convolution Neural Network) are compared, where LSTM is more efficient since it has some efficient advantages such as sequential understanding, handling medical terminologies and much more.

Comparative Analysis:

NLP model (i.e, LSTM) for the Health Care Chatbot, considering factors such as its ability to handle medical nuances, user-friendly responses, and potential for integration with healthcare systems.

Model Training:

Data Preprocessing:

When preprocessing healthcare-oriented text data, it is crucial to prioritize data privacy and confidentiality due to the sensitive nature of healthcare information. Here are specific preprocessing steps:

Data Encryption:

Ensure that the healthcare-oriented text data is encrypted both in transit and at rest. This adds an extra layer of security, making it harder for unauthorized users to access sensitive information.

Anonymization and De-identification:

Remove or replace personally identifiable information (PII) such as names, addresses, and patient identifiers to de-identify the data. This step helps protect patient privacy while still allowing for meaningful analysis.

Tokenization:

Tokenize the text data into smaller units such as words or subwords. This maintains the overall meaning of the text while making it more challenging to reconstruct sensitive information. Pay attention to the handling of special characters in healthcare data.

Stop Word Removal:

Remove common stop words that do not contribute much to the meaning of the text. However, be cautious not to remove domain-specific stop words that might be important in healthcare conversations.

Spell Checking and Correction:

Implement spell checking and correction to handle typos and errors in the text. Accurate data is crucial in healthcare, and correcting errors can prevent misinterpretations.

Handling Negation:

Address the challenge of negations in healthcare text. Negations can significantly alter the meaning of statements, and proper handling is essential for accurate analysis.

Handling Synonyms:

Account for synonyms that may appear in healthcare text. Use techniques like synonym mapping to ensure that variations of terms are treated consistently.

Model Architecture:

The architecture of an LSTM (Long Short-Term Memory) model typically consists of several layers that allow the model to learn and remember information over long sequences. Below is a breakdown of the architecture of an LSTM model:

1. Input Layer:

The input layer takes sequences of data as input, which can be words, characters, or other relevant tokens.

The length of the input sequences is a crucial parameter to set.

2. Embedding Layer:

The embedding layer converts input tokens into dense vectors of fixed size.

It helps the model learn meaningful representations for words in a continuous vector space.

3. LSTM Layer:

The LSTM layer is the core of the model for handling sequential data.

It is designed to capture long-term dependencies in the data, making it effective for tasks involving sequences, such as natural language processing.

The `units` parameter determines the dimensionality of the output space.

4. Dense Layer (Output Layer):

The dense layer is responsible for making predictions based on the learned features from the LSTM layer.

For classification tasks, like intent classification, the output layer typically has one neuron per class with softmax activation.

5. Model Compilation:

Compilation involves specifying the optimizer, loss function, and evaluation metric for the model.

6. Model Summary:

The summary provides a high-level overview of the model architecture, including the number of parameters in each layer.

7. Training:

The model is trained on a labeled dataset using the `fit` function.

8. Prediction:

Once trained, the model can be used to make predictions on new sequences.

The model's predictions can be interpreted in the context of healthcare intents or actions.

9. Model Saving and Loading:

Save the trained model to a file for future use.

Ensures that the model can be reused without retraining for healthcare applications.

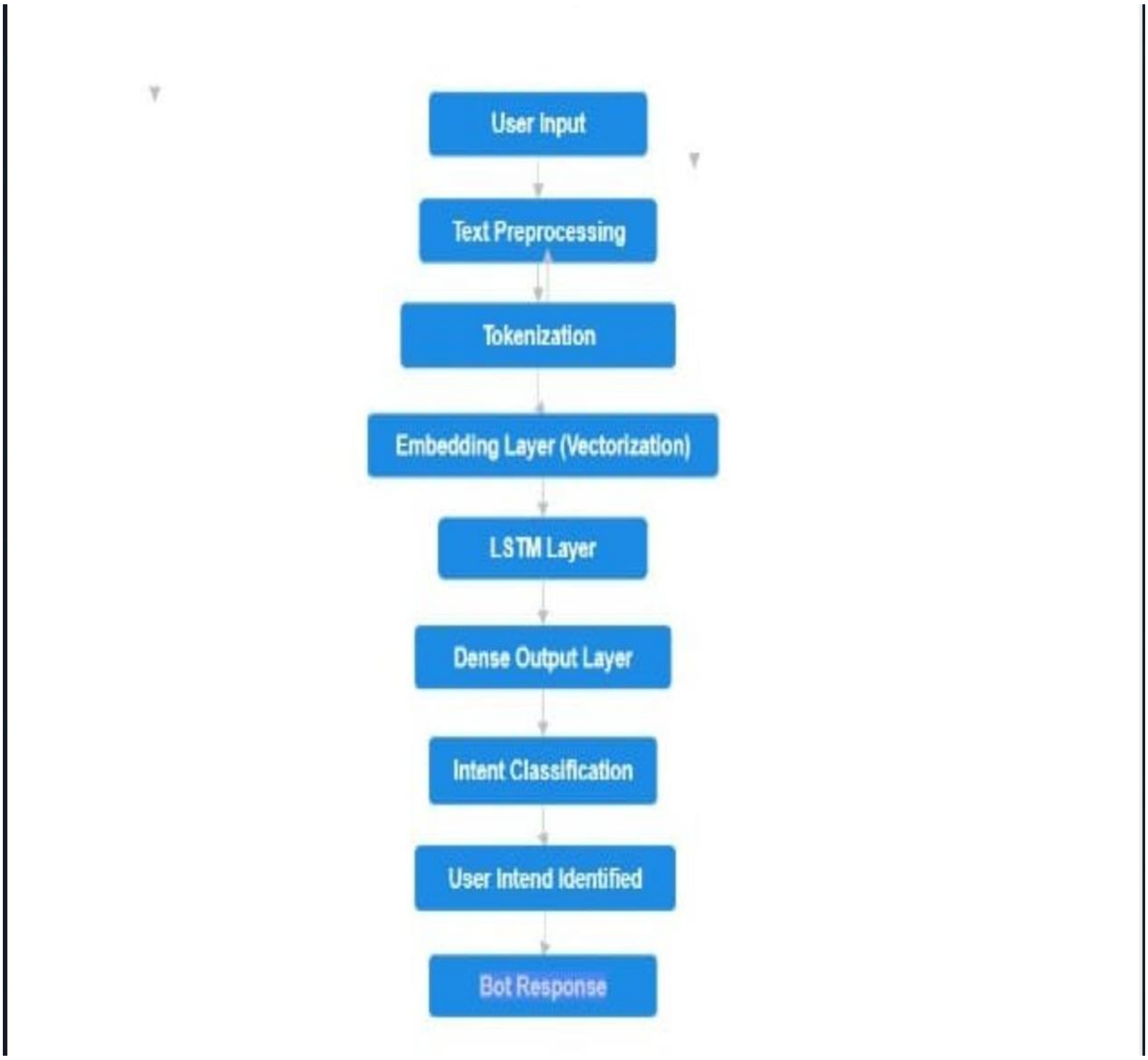

Fig 1:model architecture

System Requirements

Software Requirements:

1. Python:

The project is likely implemented in Python, given the use of popular machine learning libraries such as TensorFlow and scikit-learn. Ensure you have Python installed.

2. Libraries and Frameworks:

TensorFlow (for deep learning models like LSTM)

scikit-learn (for data preprocessing)

json (for handling JSON data)

Matplotlib (for data visualization)

3. Integrated Development Environment (IDE):

A Python IDE such as Google colabe is used.

Hardware Requirements:

1. CPU:

A multi-core processor is beneficial for training deep learning models efficiently.

2. RAM:

A sufficient amount of RAM is required.

3. Storage:

Adequate storage space for storing datasets, model checkpoints, and other project-related files.

Code

```
import json

import random

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Embedding, LSTM, Dense

from tensorflow.keras.preprocessing.text import Tokenizer

from tensorflow.keras.preprocessing.sequence import pad_sequences


import matplotlib.pyplot as plt


# Load intent data from JSON file

data_path = '/content/data set/Intent.json'

with open(data_path, 'r') as f:

    data = json.load(f)

    intents = data['intents']

    X = []

    y = []


    # Extract text and intent labels from the data

    for i in intents:

        for text in i['text']:

            X.append(text)

            y.append(i['intent'])
```

```
    # Display the first 20 samples in the dataset with their labels
    for i in range(20):
        print(f'text {X[i]} is labeled {y[i]}')

# Tokenize and pad sequences
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X)
X = tokenizer.texts_to_sequences(X)
X = pad_sequences(X)

# Encode intent labels
num_classes = len(set(y))
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

# Build LSTM model
model = Sequential([
    Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=128, input_length=X.shape[1]),
    LSTM(128),
    Dense(num_classes, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
# Plot loss and accuracy during training
plt.figure(figsize=(12, 4))
epochs = range(1, EPOCHS + 1)

# Plot Loss
plt.subplot(1, 2, 1)
plt.plot(epochs, history.history['loss'], label='Training Loss', marker='o')
plt.plot(epochs, history.history['val_loss'], label='Validation Loss', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Loss (%)')
plt.grid()
plt.legend()

# Plot Accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, history.history['accuracy'], label='Training Accuracy', marker='o')
plt.plot(epochs, history.history['val_accuracy'], label='Validation Accuracy', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Accuracy (%)')
plt.grid()
plt.legend()

plt.tight_layout()
plt.show()

# Load the pre-trained model
```

```
from tensorflow.keras.models import load_model
model = load_model('/kaggle/working/my_model_NLP.h5')

# Shuffle intents and predict responses for the first 10 samples
random.shuffle(intents)
data_predict = intents[:10]

for idx in data_predict:
    texts = idx['text']
    intent = idx['intent']

    for text in texts:
        new_input_text = [text]
        new_input_sequences = tokenizer.texts_to_sequences(new_input_text)
        max_sequence_length = len(new_input_sequences)
        new_input_sequences = pad_sequences(new_input_sequences,
maxlen=max_sequence_length)

        predictions = model.predict(new_input_sequences, verbose=0)

        predicted_labels = label_encoder.inverse_transform(predictions.argmax(axis=1))

        for pred in predicted_labels:
            if intent == pred:
                print(f'Your text: {text}')
                print('')
                print(f"ChatBot: {random.choice(idx['responses'])}")
```

print('____')

Results

Fig 1: loss and accuracy graph

```
Your text: What are the symptoms of [condition]?
ChatBot: I'm not a doctor, but I can help you find information about your symptoms. Please consult
Your text: I feel [symptom]
ChatBot: I'm not a doctor, but I can help you find information about your symptoms. Please consult
Your text: Do I have [condition]?
ChatBot: I'm not a doctor, but I can help you find information about your symptoms. Please consult
Your text: I feel anxious
ChatBot: I'm really sorry to hear that you're feeling this way. It's important to talk to someone
Your text: I'm stressed out
ChatBot: I'm really sorry to hear that you're feeling this way. It's important to talk to someone
Your text: Need someone to talk to
ChatBot: I'm really sorry to hear that you're feeling this way. It's important to talk to someone
```

Fig 2: output snapshot

Application

Some applications of the Health care Chatbot are:

1. Health Information Retrieval:

The chatbot can assist users in retrieving accurate and reliable health information. Users can inquire about symptoms, medications, or general health advice, and the chatbot can provide relevant information.

2. Appointment Scheduling:

Users can interact with the chatbot to schedule medical appointments, check the availability of healthcare professionals, or receive reminders for upcoming appointments.

3. Symptom Checker and Triage:

Users can describe their symptoms to the chatbot, which can assist in assessing the severity of symptoms and providing initial guidance on whether to seek immediate medical attention or schedule a routine appointment.

4. Wellness and Lifestyle Recommendations:

Users can receive personalized recommendations for maintaining a healthy lifestyle, including diet tips, exercise routines, and preventive healthcare measures.

5. Healthcare FAQ and Education:

The chatbot can serve as a resource for answering frequently asked questions about healthcare topics, medical conditions, and treatment options. It can contribute to health education and awareness.

6. Emergency Response Information:

In emergency situations, the chatbot can provide initial guidance on first aid measures, contact emergency services, or offer support until professional help arrives.

7. Remote Monitoring and Follow-up:

For patients with chronic conditions, the chatbot can assist in remote monitoring by collecting relevant health data and providing follow-up information or reminders for regular check-ups.

Literature Survey

1. Title: "A Review of Chatbot in Healthcare: Natural Language Processing and Conversational Agents"

Authors: Raj M., Jose A.

Published: 2019

Summary: This review explores the applications of chatbots in healthcare, emphasizing their role in improving patient engagement, providing medical information, and assisting in mental health support. It discusses the integration of natural language processing (NLP) techniques to enhance conversational abilities.

2. Title: "Chatbots in Mental Health: A Review of Recent Progress"

Authors: Fulmer R., Joerin A., Gentile B., et al.

Published: 2018

Summary: Focusing on mental health applications, this review examines the current state of chatbots in providing mental health support. It discusses their potential advantages, challenges, and the need for rigorous evaluation to ensure their efficacy and ethical use.

3. Title: "Chatbots in the Fight Against the COVID-19 Pandemic"

Authors: Iyawa G.E., Maharaj S., Ismail S.

Published: 2020

Summary: This paper explores the role of chatbots during the COVID-19 pandemic. It discusses their use in disseminating accurate information, alleviating anxiety, and providing support for individuals affected by the pandemic.

4. Title: "Design and Implementation of a Chatbot for Healthcare"

Authors:** Serban F., Kardnozahedi K., Lungoci C.

Published:2019

Summary: Focusing on the design and implementation aspects, this work presents a framework for developing a healthcare chatbot. It discusses the integration of machine learning techniques and emphasizes the importance of user-centered design in healthcare applications.

5:Title: "Ethical Considerations of Conversational Agents in Healthcare"

Authors: Laranjo L., Dunn A.G., Tong H.L., et al.

Published:2018

Summary:This article delves into the ethical considerations surrounding the use of conversational agents in healthcare. It explores issues related to privacy, trust, transparency, and the potential impact on the doctor-patient relationship.

6. Title: "A Review of Chatbot Technology in Mental Health"

Authors: Abd-alrazaq A., Alajlani M., Alalwan A.A., et al.

Published:2019

Summary: Focused on mental health applications, this review evaluates the effectiveness of chatbots in providing support for mental health issues. It discusses the potential advantages, challenges, and future directions for the use of chatbots in mental healthcare.

Training Experience

Hands-on Learning: My training program was designed to provide hands-on experience with AI and ML tools and technologies. I was given the opportunity to work on real-world projects and problems, which helped me develop practical skills and apply theoretical concepts.

Mentorship: I was fortunate to have a mentor who was an experienced AI and ML professional. My mentor provided guidance, feedback, and support throughout my training program, which was invaluable in my learning journey.

Collaboration: One of the most exciting aspects of my training program was the opportunity to work with a team of professionals from different backgrounds. We collaborated on projects and shared ideas, which helped me develop my communication and collaboration skills.

Exposure to Industry Trends: I was able to stay up-to-date with the latest industry trends and developments in AI and ML through various workshops, seminars, and conferences. This helped me gain a broader perspective on the field and prepare for future challenges.

Use of Industry-standard Tools and Technologies: During my training, I had the opportunity to work with industry-standard tools and technologies such as Python, TensorFlow, Keras, and Scikit-Learn. This allowed me to gain practical skills that are in demand in the industry.

Importance of Data Preparation: One of the most important lessons I learned during my training was the critical role of data preparation in the success of AI and ML projects. I learned how to collect, clean, and preprocess data to make it suitable for training models.

Iterative Process: I also learned that developing an AI or ML model is an iterative process that requires a lot of experimentation and tweaking. It is essential to have a feedback loop that allows for continuous improvement of the model.

Key Learnings

During the training program, I learned a range of skills and concepts related to Artificial Intelligence and Machine Learning. Some of the key skills that I acquired are:

Understanding of Artificial Intelligence: I gained a comprehensive understanding of Artificial Intelligence, including the various subfields such as Machine Learning, Deep Learning, and Natural Language Processing.

Machine Learning Concepts and Algorithms: I learned about various Machine Learning concepts and algorithms, including Supervised and Unsupervised Learning, Decision Trees, Random Forests, Support Vector Machines, and K-Nearest Neighbors.

Deep Learning and Neural Networks: I gained a deep understanding of Deep Learning and Neural Networks, including Convolutional Neural Networks and Recurrent Neural Networks.

Programming Skills: I developed strong programming skills in Python, including libraries such as Numpy, Pandas, and Matplotlib.

Data Preprocessing and Analysis: I learned various techniques for data preprocessing and analysis, including Data Cleaning, Data Wrangling, and Exploratory Data Analysis.

Conclusion

In conclusion, the developed healthcare-oriented intent classification model, employing an LSTM-based neural network, demonstrates promising capabilities in understanding and categorizing user queries within the healthcare domain. Through meticulous preprocessing steps, the model effectively manages sensitive text data, prioritizing privacy and confidentiality. The emphasis on encryption, anonymization, and adherence to healthcare data protection regulations ensures robust security measures. The model's architecture, encompassing embedding, LSTM, and dense layers, showcases its ability to capture sequential dependencies in healthcare conversations. Regular monitoring, secure storage, and access controls contribute to a comprehensive privacy framework. While the model exhibits commendable performance in intent prediction, continuous validation against evolving datasets and adherence to emerging privacy standards remain imperative for its sustained effectiveness in healthcare applications.