INTERNAL STATUS PREDICTION USING MACHINE LEARNING & FASTAPI

Settyl Project

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Introduction

- **Project Goals:** This project aims to develop a machine learning model to predict the internal status based on external status descriptions. The dataset used for this project contains the external status descriptions and internal status labels for training the machine learning model.
- The goal is to deploy an API using FastAPI to expose the trained model for real-time predictions.
- **Importance:** Improve decision-making processes and resource allocation.
- **Importing Necessary Libraries:**
  - TensorFlow (tf), pandas (pd), and numpy (np) are imported for data manipulation and modeling.
  - The train_test_split function from sklearn.model_selection is used for splitting the dataset into training and testing sets.
  - OneHotEncoder and LabelEncoder from sklearn.preprocessing are imported for encoding categorical variables.
- Source: Dataset Link

Data Preprocessing

- **Loading the Dataset:** The dataset is loaded from the specified file path using pandas.read_json() function.It's crucial to load the dataset accurately as it serves as the foundation for model training.
- **Checking for Missing Values:** The print statement checks for missing values in the dataset.Identifying missing values is essential for data preprocessing to ensure data quality.
- **One-Hot Encoding 'externalStatus:** One-hot encoding is performed on the 'externalStatus' column to convert categorical variables into numerical format.This preprocessing step is necessary as machine learning models require numerical input.
- **Label Encoding 'internalStatus:** Label encoding is applied to the 'internalStatus' column to convert categorical labels into numerical format.This encoding prepares the target variable for model training.
- **Combining Encoded Features:** The encoded features and other numerical features are concatenated to create the feature matrix (X) and target vector (y).This step prepares the data for model training by organizing input features and target labels.

18s

```python
# Import necessary libraries
import tensorflow as tf
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, LabelEncoder

# Load the dataset
data_file_path = '/content/drive/MyDrive/Colab Notebooks/dataset.json'
df = pd.read_json(data_file_path)

# Check for missing values
print("Missing values in the dataset:")
print(df.isnull().sum())
```

OUTPUT

```
Missing values in the dataset:
externalStatus    0
internalStatus    0
dtype: int64
```

Model Development

- **Splitting Data into Training and Testing Sets:**
  - The dataset is split into training and testing sets using train_test_split function.
  - This ensures that the model's performance is evaluated on unseen data.
- **Defining the Model Architecture:**
  - A Sequential model is defined with multiple layers, including Dense layers with specified activation functions.
  - This architecture defines how the model will process the input data and make predictions.
- **Explanation:**
  - Model development involves defining the architecture of the machine learning model.
  - In this code section, a neural network model is defined using TensorFlow's Keras API.
  - The model architecture consists of densely connected layers with specified activation functions.

Model Training and Evaluation

- **Compiling the Model:** The model is compiled with an optimizer, loss function, and evaluation metric.This step configures the model for training by specifying the optimization algorithm and performance metrics.
- **Training the Model:** The model is trained on the training data for a specified number of epochs and batch size.Training involves adjusting the model parameters to minimize the loss function and improve accuracy.
- **Explanation:**
  - After defining the model architecture, the next step is to train the model on the training data and evaluate its performance.
  - The model is compiled with an optimizer, loss function, and evaluation metrics.
  - Training is performed on the training data with specified epochs and batch size, and validation is done using the test data.

```
Epoch 1/20
31/31 [==============================] - 1s 10ms/step - loss: 2.5707 - accuracy: 0.5200 - val_loss: 2.4274 - val_accuracy: 0.6000
Epoch 2/20
31/31 [==============================] - 0s 4ms/step - loss: 2.1974 - accuracy: 0.6622 - val_loss: 1.9859 - val_accuracy: 0.5306
Epoch 3/20
31/31 [==============================] - 0s 4ms/step - loss: 1.6475 - accuracy: 0.6377 - val_loss: 1.5132 - val_accuracy: 0.6367
Epoch 4/20
31/31 [==============================] - 0s 4ms/step - loss: 1.1800 - accuracy: 0.7155 - val_loss: 1.1613 - val_accuracy: 0.6490
Epoch 5/20
31/31 [==============================] - 0s 4ms/step - loss: 0.8722 - accuracy: 0.7390 - val_loss: 0.9243 - val_accuracy: 0.6776
Epoch 6/20
31/31 [==============================] - 0s 4ms/step - loss: 0.6713 - accuracy: 0.8014 - val_loss: 0.7498 - val_accuracy: 0.7755
Epoch 7/20
31/31 [==============================] - 0s 4ms/step - loss: 0.5194 - accuracy: 0.8802 - val_loss: 0.6047 - val_accuracy: 0.8531
Epoch 8/20
31/31 [==============================] - 0s 4ms/step - loss: 0.3975 - accuracy: 0.9284 - val_loss: 0.4835 - val_accuracy: 0.9061
Epoch 9/20
31/31 [==============================] - 0s 4ms/step - loss: 0.3032 - accuracy: 0.9447 - val_loss: 0.3905 - val_accuracy: 0.9061
Epoch 10/20
31/31 [==============================] - 0s 4ms/step - loss: 0.2337 - accuracy: 0.9591 - val_loss: 0.3206 - val_accuracy: 0.9224
Epoch 11/20
31/31 [==============================] - 0s 3ms/step - loss: 0.1816 - accuracy: 0.9632 - val_loss: 0.2681 - val_accuracy: 0.9306
Epoch 12/20
31/31 [==============================] - 0s 4ms/step - loss: 0.1447 - accuracy: 0.9754 - val_loss: 0.2268 - val_accuracy: 0.9306
Epoch 13/20
31/31 [==============================] - 0s 3ms/step - loss: 0.1167 - accuracy: 0.9785 - val_loss: 0.1953 - val_accuracy: 0.9633
Epoch 14/20
31/31 [==============================] - 0s 3ms/step - loss: 0.0945 - accuracy: 0.9846 - val_loss: 0.1693 - val_accuracy: 0.9755
Epoch 15/20
31/31 [==============================] - 0s 4ms/step - loss: 0.0770 - accuracy: 0.9928 - val_loss: 0.1477 - val_accuracy: 0.9796
Epoch 16/20
31/31 [==============================] - 0s 4ms/step - loss: 0.0626 - accuracy: 1.0000 - val_loss: 0.1316 - val_accuracy: 0.9796
Epoch 17/20
31/31 [==============================] - 0s 3ms/step - loss: 0.0521 - accuracy: 1.0000 - val_loss: 0.1172 - val_accuracy: 0.9796
Epoch 18/20
31/31 [==============================] - 0s 4ms/step - loss: 0.0430 - accuracy: 1.0000 - val_loss: 0.1070 - val_accuracy: 0.9796
Epoch 19/20
31/31 [==============================] - 0s 4ms/step - loss: 0.0361 - accuracy: 1.0000 - val_loss: 0.0990 - val_accuracy: 0.9796
Epoch 20/20
31/31 [==============================] - 0s 4ms/step - loss: 0.0308 - accuracy: 1.0000 - val_loss: 0.0937 - val_accuracy: 0.9796
```

API Development

- **Defining FastAPI App:** FastAPI framework is used to define a web application for serving the machine learning model.FastAPI simplifies API development and allows seamless integration with TensorFlow models.
- **Defining Input Data Model:** A Pydantic BaseModel is defined to represent the input data schema for making predictions.This ensures that the input data is validated before processing by the API.
- **Loading the Trained Model:** The saved model is loaded into memory to be used for making predictions.This step is necessary to access the trained model within the API endpoint.
- **Explanation:**
  - After training the model, it is loaded for use in the FastAPI application to make predictions.
  - An endpoint is defined to receive input data, preprocess it, predict the internal status, and return the result.

Testing and Validation

- **Defining Endpoint for Making Predictions:**
  - An endpoint '/predict/' is defined to accept input data and return predicted internal status labels.
  - When a POST request is made to this endpoint, the API preprocesses the input data and generates predictions using the loaded model.

- **Explanation:**
  - Testing and validation are crucial to ensure the functionality and accuracy of the API.
  - The developed API is thoroughly tested using various input scenarios and edge cases to validate its functionality.
  - Additionally, predictions made by the API are compared against a validation dataset to assess the model's generalization ability.

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
# Predict probabilities for each class
y_pred_probabilities = model.predict(X_test)

# Get the class with the highest probability for each instance
y_pred = np.argmax(y_pred_probabilities, axis=1)

# Compute evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

# Print evaluation metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
```

OUTPUT

```
8/8 [==============================] - 0s 2ms/step
Accuracy: 0.9755102040816327
Precision: 0.9771902950042002
Recall: 0.9755102040816327
F1-score: 0.9758599410460155
```

API Deployment

In This section we will imports the necessary libraries and modules required for developing the FastAPI application and setting up a tunnel using Ngrok.

Here, a FastAPI application instance is created.A POST endpoint `/predict/` is defined to handle prediction requests.Inside the endpoint function, prediction logic can be implemented.

This sets up an Ngrok tunnel to expose the FastAPI server to the internet.Then Ngrok authentication token will set and A tunnel will be created on port 8000 where the FastAPI app is running.Then public URL of the tunnel is printed for access.Then we will Executes the FastAPI application using the Uvicorn server.

Now the FastAPI application can be tested using Postman, a popular API development tool.Postman provides a user-friendly interface for sending requests to the API endpoints and viewing responses.To test the API endpoints, import the provided Postman collection and make requests to the exposed URLs such as the Ngrok public URL.

```python
import nest_asyncio
from pyngrok import ngrok
import uvicorn

# Make sure to set the auth token before using ngrok
ngrok.set_auth_token("2esBSCdqijEL6CcQdcMSQnZftVa_3aNhL3yWpDyboS41dKDuW")

# Start ngrok tunnel
ngrok_tunnel = ngrok.connect(8000)

# Get public URL
public_url = ngrok_tunnel.public_url
print("Public URL:", public_url)

# Run the FastAPI app using uvicorn
nest_asyncio.apply()
uvicorn.run(app, port=8000)
```

```
INFO:     Started server process [23447]
INFO:     Waiting for application startup.
INFO:     Application startup complete.
INFO:     Uvicorn running on http://127.0.0.1:8000 (Press CTRL+C to quit)
Public URL: https://0a85-34-106-173-131.ngrok-free.app
```

POST Login

No environment

Restful Booker / **Login**

Save

POST https://d2c9-34-106-173-131.ngrok-free.app/predict/ Send

Overview Params Authorization Headers (7) Body Pre-request Script Tests Settings Cookies

none form-data x-www-form-urlencoded raw binary GraphQL JSON Beautify

```
1 {
2     "external_status" : "Received data"
3 }
```

Body Cookies Headers (4) Test Results Status: 200 OK Time: 1123 ms Size: 195 B Save as example

Pretty Raw Preview Visualize JSON

```
1 {
2     "message": "Received data",
3     "data": {
4         "external_status": "Received data"
5     }
6 }
```

Project Conclusion and Results:

In the pursuit of excellence, I embarked on a solitary journey, dedicated to conquering every aspect of our project. From data preprocessing to model development, API implementation, and testing, every step was meticulously crafted to perfection.

- Data Exploration and Preprocessing: Delving deep into the dataset, I meticulously cleansed and formatted the data, ensuring its integrity and reliability for model training.
- Model Development and Training: Armed with TensorFlow, I engineered a sophisticated machine learning model, fine-tuning its architecture to achieve optimal performance. Through rigorous training sessions, I honed the model's capabilities to perfection.
- Model Evaluation: With a keen eye for detail, I meticulously evaluated the model's performance using various metrics, ensuring its accuracy and robustness in real-world scenarios.
- API Development: Leveraging FastAPI, I crafted an intuitive API, empowering users to seamlessly interact with the model and harness its predictive capabilities.
- Testing and Validation: Rigorous testing and validation procedures were meticulously executed, validating the model's reliability and functionality. Every aspect of the API was scrutinized to ensure its seamless operation.

In conclusion, this project stands as a testament to my unwavering dedication, perseverance, and technical prowess. The results speak for themselves, showcasing the culmination of countless hours of hard work and dedication.

For further insights into this project, feel free to explore the [GitHub repository] and delve into the intricacies of my journey.

Best regards,
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