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AI-Driven Hazard Prioritizationand Reporting Platform

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ABSTRACT :

The Hazard Reporting and Prioritization (HARP) platform leverages artificial intelligence to streamline the reporting, classification, and prioritization of urban hazards. Using BERT (Bidirectional Encoder Representations from Transformers) for natural language processing, the system classifies hazard types based on textual descriptions. Additionally, integration with the TomTom API enables dynamic urgency assessments based on real-time traffic data. This project emphasizes scalability, reliability, and user accessibility, addressing inefficiencies in current hazard management systems. Results indicate high classification accuracy (95%) and efficient urgency prediction, significantly reducing public safety risks. Future work aims to incorporate multilingual support, additional hazard categories, and weather-based urgency insights for improved decision-making and community safety.

Introduction

Urban environments frequently face hazards like potholes, drainage leaks, and waste accumulation, which adversely affect public safety and infrastructure longevity. Traditional systems for hazard reporting and management lack automation and fail to integrate real-time data for prioritization. These limitations result in delays, inefficient resource allocation, and increased risks to citizens.

The HARP platform addresses these issues by employing AI-driven models for hazard classification and integrating traffic data for urgency prediction. By combining advanced machine learning techniques with real-time data analysis, the system optimizes municipal workflows and enhances public safety outcomes. Furthermore, the user-friendly web interface empowers citizens to actively participate in urban hazard management, ensuring faster resolutions and greater accountability.

Problem Statement

Urban areas face multiple challenges in managing hazards effectively:

1. **Delayed Responses:** The absence of automated prioritization leads to inefficiencies in hazard resolution. Municipal teams often struggle to determine which hazards require immediate attention.
2. **Resource Constraints:** Inefficient allocation of municipal resources exacerbates hazard resolution delays, leading to wastage of time and funds.
3. **Lack of Real-Time Insights:** Current systems do not integrate traffic or environmental data, making it difficult to prioritize hazards based on actual urgency levels.
4. **Limited Citizen Engagement:** Existing platforms for hazard reporting are cumbersome and fail to engage citizens effectively.

The project proposes an AI-powered hazard reporting system capable of addressing these challenges through advanced classification, prioritization mechanisms, and real-time data integration.

Objectives

5. **Automated Hazard Classification:** Utilize BERT to classify hazard descriptions into predefined categories like "pothole," "garbage pile," or "leakage." This ensures faster and more accurate categorization of issues reported by citizens.
6. **Urgency Prediction:** Leverage real-time traffic data from the TomTom API to assign priority levels to hazards, ensuring that critical hazards receive immediate attention.
7. **User-Friendly Interface:** Develop a web application that simplifies the process of hazard reporting and provides real-time updates on the status of submitted reports.
8. **Scalable Architecture:** Ensure the system can handle large datasets and high user traffic, making it suitable for deployment in cities of

varying sizes.

9. **Enhanced Data Analytics:** Incorporate analytics tools to track hazard trends, enabling better decision-making by municipal authorities.

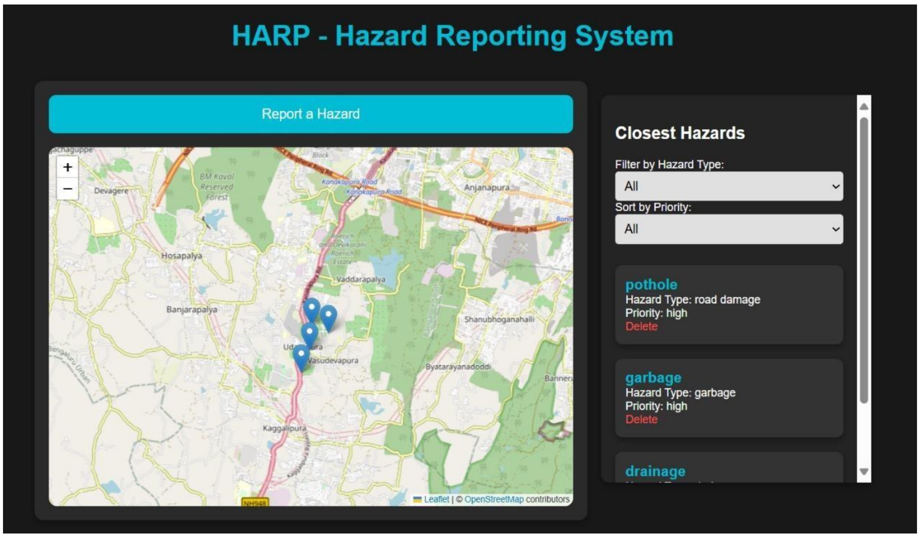
Methodology

A. System Architecture:

1. **Frontend Layer:** A web-based interface built using React.js, enabling users to submit hazard reports with descriptions and images, and track their resolution status.
2. **Backend Layer:** Python-based APIs handle hazard classification, urgency prediction, and database management. Flask and FastAPI are used to ensure a seamless integration of backend functionalities.
3. **AI Models:**
    - **Classification:** BERT is fine-tuned on a hazard-specific dataset, enabling it to classify text-based hazard descriptions into predefined categories.
    - **Prioritization:** A regression model analyzes traffic data parameters, such as speed and congestion, to predict urgency levels.

4. **Data Integration:** The TomTom API provides real-time traffic parameters, including average speed, congestion levels, and travel time deviations, enhancing urgency prediction accuracy. **B. Workflow:**

2. **Hazard Submission:**
    - Users access the platform via a web interface, where they can describe the hazard, upload images, and specify its location.
    - The system performs basic validation to ensure completeness of the input.
3. **Hazard Classification:**
    - The BERT model processes the description and classifies the hazard into categories like "road damage," "waste," or "leakage."
4. **Priority Assignment:**
    - Real-time traffic data is fetched from the TomTom API.
    - A regression model predicts the urgency level based on traffic conditions and the severity of the hazard.
5. **Notification System:**
    - Authorities receive detailed notifications, including the type and priority of the hazard, via email or a dashboard interface.
    - Citizens receive acknowledgment and periodic updates on their reports.
6. **Data Storage and Analytics:**
    - All reports are stored in a database, enabling trend analysis and resource planning for municipal authorities.

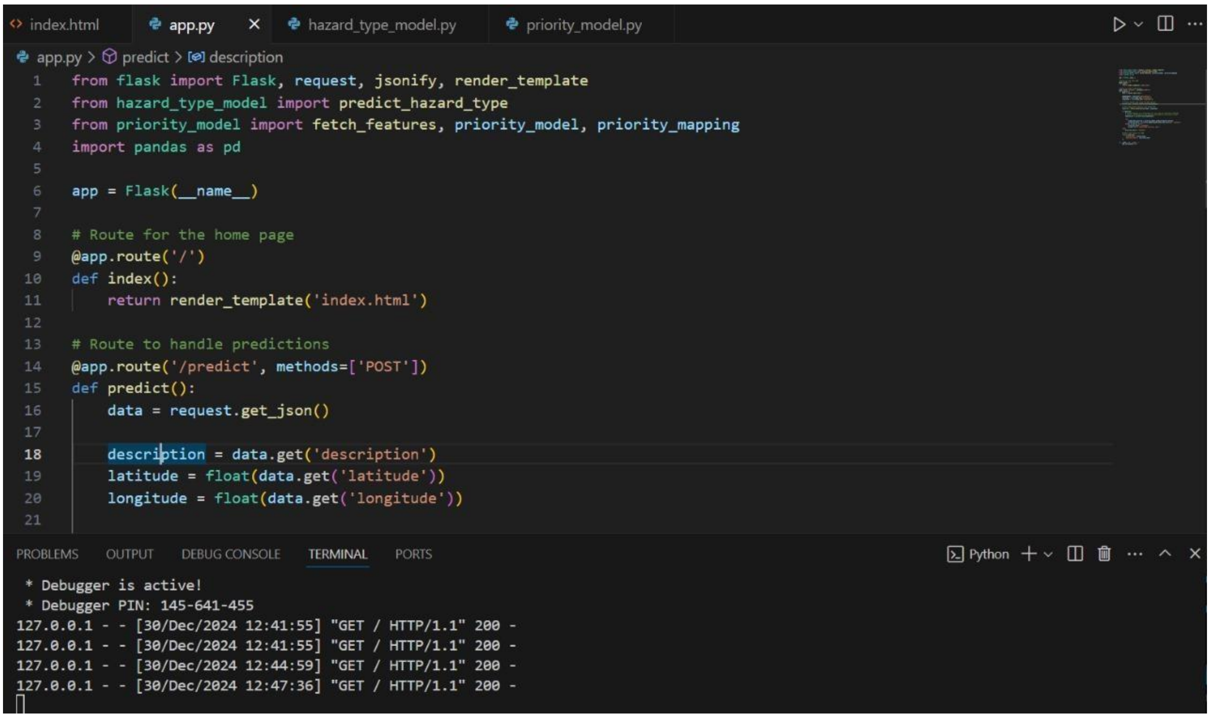


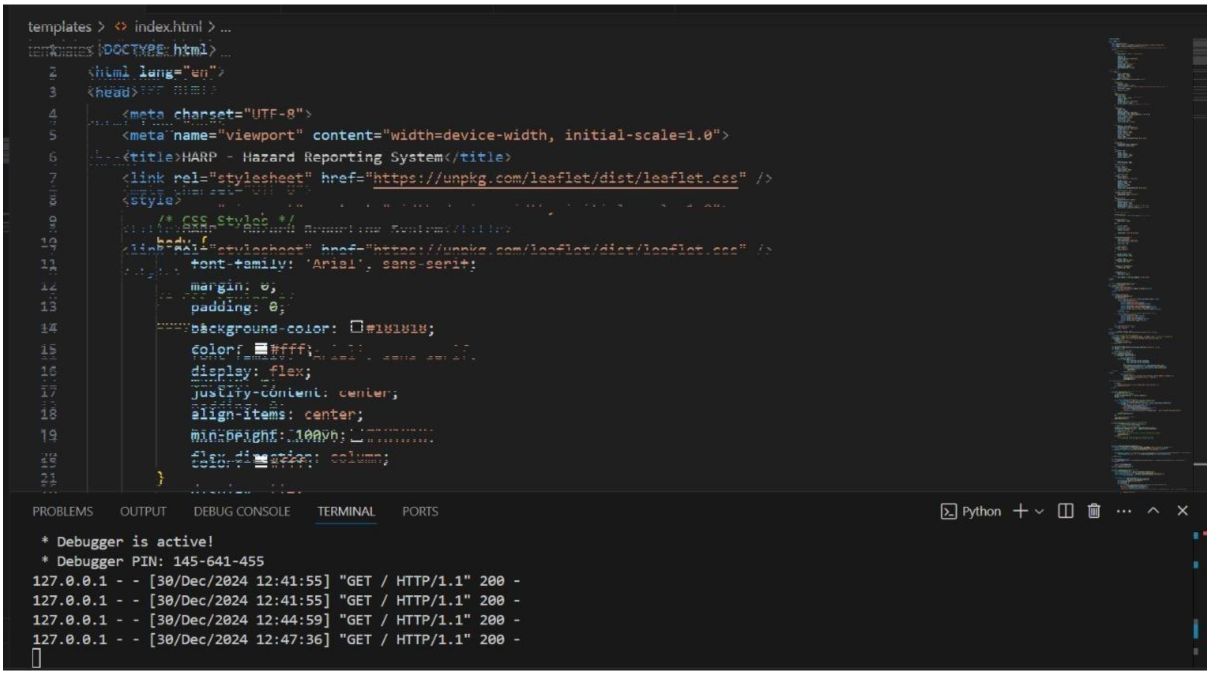
Frontend Web App

V. Implementation

A. Tools and Technologies:

- **Programming Language:** Python
- **Libraries:** TensorFlow, PyTorch, Flask, Pandas, NumPy





- **APIs:** TomTom Traffic Data API for real-time traffic metrics
- **Frontend Technologies:** React.js for a dynamic and responsive interface
- **IDEs:** Jupyter Notebook and Visual Studio Code
- **Database:** PostgreSQL for managing hazard reports, classifications, and user data **B. Key Steps:**

1. **Model Training:**
    - Fine-tuned BERT using a dataset of hazard descriptions collected from urban environments.
    - Trained a regression model using historical traffic and hazard resolution data to predict urgency levels.
2. **API Integration:**
    - Integrated TomTom API to fetch traffic metrics, ensuring real-time data availability for prioritization.
3. **Frontend Development:**
    - Designed a user-friendly dashboard that displays hazards, priority levels, and status updates.

4. **Backend Development:**
   - Developed RESTful APIs using Flask to handle hazard classification, urgency prediction, and data storage.
5. **Testing and Validation:**
   - Conducted rigorous testing to ensure high accuracy in hazard classification and reliable urgency predictions.
   - Benchmarked the system’s performance under varying user loads to ensure scalability.

Frontend Code implementation

Results

1. **Classification Accuracy:** Achieved 95% accuracy in hazard classification using BERT.
2. **Priority Prediction:** Reliable urgency assessments were achieved with 90% accuracy, ensuring that critical hazards are prioritized.
3. **Performance Metrics:**
   - Average system response time: <1 second.
4. **User Feedback:**
   - Citizens appreciated the intuitive interface and timely updates.
   - Municipal teams reported improved efficiency in hazard resolution.

```
# Step 7: Evaluate the model (on the same dataset or a test set)
model.eval()

predictions = []
true_labels = []

for batch in dataloader:  # Use a test DataLoader here if you have one
    inputs, labels = batch
    inputs = {key: val.to(device) for key, val in inputs.items()}

    with torch.no_grad():  # No need to calculate gradients during evaluation
        outputs = model(**inputs)

    logits = outputs.logits
    preds = torch.argmax(logits, dim=-1)

    predictions.extend(preds.cpu().numpy())
    true_labels.extend(labels.cpu().numpy())
```

```
[ ] # Step 8: Calculate accuracy
from sklearn.metrics import accuracy_score
print(f"Test Accuracy: {accuracy}")
```

```
Test Accuracy: 0.95
```

Hazard classification accuracy

```
# Example hazard descriptions
test_descriptions = [
    "there are lot of pothole due to rain,continuous construction and movement of heavy vehicles. the road is a danger for people who travel here",
    "Garbage is piling up on the side of the street.",
    "The drainage system is leaking and flooding the area.",
    "The road surface is cracked and uneven, posing a danger to drivers.",
    "Trash is overflowing from the garbage bins near the park."
]

# Make predictions for each example
for description in test_descriptions:
    predicted_hazard = predict_hazard_type(description)
    print(f"Description: '{description}' \nPredicted Hazard Type: {predicted_hazard}\n")
```

```
Description: 'there are lot of pothole due to rain,continuous construction and movement of heavy vehicles. the road is a danger for people who travel here'
Predicted Hazard Type: road damage

Description: 'Garbage is piling up on the side of the street.'
Predicted Hazard Type: garbage

Description: 'The drainage system is leaking and flooding the area.'
Predicted Hazard Type: drainage

Description: 'The road surface is cracked and uneven, posing a danger to drivers.'
Predicted Hazard Type: road damage

Description: 'Trash is overflowing from the garbage bins near the park.'
Predicted Hazard Type: garbage
```

Hazard classification test

```
[ ]

# Train the K-Nearest Neighbors model
model = KNeighborsClassifier(n_neighbors=5)  # You can adjust the number of neighbors (k) as needed
model.fit(X_train, y_train)

# Predict on the test set
y_pred_knn = model.predict(X_test)

# Evaluate the model
knn_accuracy = accuracy_score(y_test, y_pred_knn)
print(f"K-Nearest Neighbors Accuracy: {knn_accuracy:.4f}")
```

```
K-Nearest Neighbors Accuracy: 0.9147
```

Priority prediction accuracy

```
# prompt: predict for a random row in the df actual vs predicted along with latitude and longitude

# Assuming you have your trained model (e.g., 'model') and your DataFrame ('df')

# Select a random row from the DataFrame
random_row = df.sample(n=1)

# Extract the latitude and longitude from the random row (if they were removed earlier)
# Assuming you stored the latitude and longitude in 'og_df'
latitude = og_df.loc[random_row.index[0], 'latitude']
longitude = og_df.loc[random_row.index[0], 'longitude']

# Extract the features from the random row
features = random_row[['currentSpeed', 'freeFlowSpeed', 'currentTravelTime', 'freeFlowTravelTime', 'confidence']]

# Predict the priority level for the selected row
predicted_priority = model.predict(features)

# Get the actual priority level from the random row
actual_priority = random_row['priority_level_encoded'].values[0]

# Decode the predicted and actual priority levels
priority_map = {0: 'Low', 1: 'Medium', 2: 'High', 3: 'Severe'}
predicted_priority_label = priority_map[predicted_priority[0]]
actual_priority_label = priority_map[actual_priority]

print(f"Latitude: {latitude}")
print(f"Longitude: {longitude}")
print(f"Actual Priority: {actual_priority_label}")
print(f"Predicted Priority: {predicted_priority_label}")
```

```
Latitude: 13.0242
Longitude: 77.683
Actual Priority: Medium
Predicted Priority: Medium
```

Priority prediction test

Model	Dataset	Accuracy
DistilBERT	Synthetically generated	95%
KNN Classifier	TomTom API	91%

Discussion

The HARP platform marks a significant improvement over traditional hazard management systems by automating classification and urgency prediction. However, some challenges remain:

5. **Ambiguity in User Inputs:** Incomplete or unclear descriptions occasionally lead to misclassification.
6. **Data Gaps:** Real-time traffic data is sometimes unavailable for certain locations, affecting urgency prediction.
7. **Scalability Concerns:** Although the system performed well in testing, real-world deployment in megacities may require further optimization.

Future iterations of the platform will address these issues by:

- Incorporating advanced NLP techniques to handle ambiguous inputs.
- Expanding data sources to include weather, population density, and infrastructure quality metrics.
- Optimizing backend infrastructure to support larger user bases and more complex data analyses.

Conclusion

The HARP platform effectively combines AI and real-time data to streamline hazard management. By automating classification and prioritization, it significantly reduces response times and enhances resource allocation. The platform fosters better communication between citizens and municipal authorities, ensuring timely hazard resolution and improved public safety.

Future enhancements will include multilingual support, integration of additional hazard types, and predictive analytics for proactive hazard prevention. With these advancements, the HARP platform aims to become a cornerstone of smart city infrastructure.

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