SUPPLY CHAIN DISRUPTION PREDICTOR

CS19643 – FOUNDATIONS OF MACHINE LEARNING

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BONAFIDE CERTIFICATE

Certified that this Project titled "SUPPLY CHAIN DISRUPTION PREDICTOR" is the bonafide work of "SANJEEV KANTH S (2116220701250)" who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today's globally interconnected marketplace, supply chain systems are the backbone of industries, yet they remain highly vulnerable to unforeseen disruptions. These disruptions—caused by extreme weather events, labor strikes, political instability, or infrastructural failures—can lead to delayed deliveries, increased costs, and diminished customer satisfaction. Predicting such disruptions in advance can allow companies to mitigate risks, optimize operations, and improve resilience. This project presents the design and implementation of a **Supply Chain Disruption Predictor**, a machine learning-based model aimed at forecasting potential disruptions using structured event and environmental data.

The model takes inputs such as the type of disruptive event, the severity of associated weather conditions, and the geographical location to predict whether a supply chain disruption is likely to occur. The project began with data synthesis and preprocessing steps, including handling missing values, encoding categorical variables, and balancing the dataset. A Random Forest Classifier was selected due to its ability to handle categorical inputs, resist overfitting, and provide insights into feature importance. We further improved performance by conducting hyperparameter tuning using grid search, optimizing parameters like the number of estimators, tree depth, and splitting criteria.

The trained model achieved an accuracy of **94%**, showing strong predictive capability with high precision and recall scores. Feature importance analysis revealed that weather severity was the most influential factor, followed by the type of event and location. For ease of use, the system can be integrated with a graphical user interface (GUI) built using tkinter , allowing users to input scenario parameters and receive real-time predictions.

This project demonstrates how data-driven decision-making tools can enhance supply chain resilience. With further improvements, such as real-time data integration and natural language processing (NLP) for textual news inputs, this tool can serve as a comprehensive decision support system for supply chain risk management in industries like manufacturing, logistics, retail, and healthcare.

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CHAPTER 1

1.INTRODUCTION

In the increasingly globalized and dynamic business environment, supply chains are becoming more complex and interconnected than ever before. While this interconnectedness brings numerous efficiencies and cost benefits, it also exposes organizations to a wide range of risks and disruptions. These disruptions—ranging from natural disasters and extreme weather to political unrest, economic crises, and logistical bottlenecks—can cause significant financial and operational setbacks for companies.

Traditionally, supply chain risk management has been reactive, addressing problems only after they occur. However, the need for proactive disruption management has grown immensely with the increasing frequency and severity of supply chain interruptions. Businesses now seek predictive tools that can forecast potential disruptions and allow for preemptive measures. This is where machine learning can play a transformative role.

This project, titled **Supply Chain Disruption Predictor**, aims to address this gap by leveraging machine learning techniques to predict the likelihood of disruptions based on various input features such as the type of event, weather severity, and geographical location. By analyzing historical patterns and trends, the system can assist businesses in identifying potential vulnerabilities in their supply chains and making informed decisions to mitigate risk.

The project utilizes a Random Forest Classifier—chosen for its robustness, interpretability, and ability to handle both categorical and numerical data effectively. The model is trained on a synthesized dataset created to simulate real-world scenarios of supply chain disruption events. Preprocessing steps such as data cleaning, encoding, balancing, and hyperparameter tuning are applied to ensure that the model performs efficiently and accurately.

With an accuracy of 94%, the model demonstrates its potential to serve as a decision-support tool. Additionally, this system is designed with an easy-to-use interface that can be implemented such as tkinter, , enabling seamless interaction for business users.

In essence, this project showcases how artificial intelligence can be integrated into supply chain management to enhance its resilience, reduce downtime, and enable smarter, faster decision-making in the face of uncertainty.

As global trade continues to expand, the resilience of supply chains has become a critical factor in maintaining competitive advantage. Organizations need tools that not only detect disruptions but anticipate them in advance. By integrating machine learning with supply chain analytics, this project provides a strategic approach to risk management—transforming reactive responses into proactive strategies that ensure continuity, reduce losses, and improve overall operational efficiency.

CHAPTER 2

2.LITERATURE SURVEY

Supply chain disruption prediction has been an active area of research, particularly following major global crises such as the COVID-19 pandemic and geopolitical conflicts that severely impacted global logistics. Researchers and industries alike have focused on integrating artificial intelligence (AI), machine learning (ML), and data analytics to enhance visibility, forecasting, and decision-making across supply chains.

Several studies have proposed machine learning models, including Random Forest, Support Vector Machines (SVM), and Neural Networks, for disruption prediction. For instance, Ivanov et al. (2020) explored the use of stochastic simulations and ML models to detect and mitigate disruptions caused by pandemic scenarios. These models leverage historical data, sensor inputs, and third-party signals to predict the likelihood and impact of disruptions.

According to Tang and Veelenturf (2019), external unstructured data like news articles, social media signals, and weather alerts significantly contribute to disruption detection. Text classification models such as NLP-based sentiment analysis and event recognition from news headlines have shown promise in enhancing supply chain intelligence.

Weather severity is often cited as a key predictor in logistics and transportation disruptions. In a study by Singh et al. (2018), weather-related delays were found to be responsible for over 30% of shipment slowdowns in maritime and trucking industries. Integration of meteorological data into ML models has become a standard practice for increasing prediction accuracy.

Research by Ghosh and Mukherjee (2021) emphasized the importance of categorical encoding techniques (like one-hot and label encoding) and feature scaling in improving the performance of classification models for supply chain analysis. These preprocessing methods reduce model bias and variance, making models more generalizable.

Random Forest has emerged as a reliable algorithm in this field due to its robustness to noise, ability to handle missing data, and interpretability. It is especially effective in heterogeneous datasets common in supply chain applications, as noted in a comparative study by Liu et al. (2022), where Random Forest outperformed other algorithms in disruption classification tasks

Recent advancements in real-time analytics and big data integration have significantly improved the responsiveness of supply chain disruption detection systems. As highlighted by Chopra and Sodhi (2014), resilient supply chains require not just robust infrastructure but intelligent systems capable of proactive risk mitigation. Modern studies have explored the integration of structured data (e.g., shipment logs, delivery records) with unstructured data (e.g., social media trends, political news) to provide comprehensive early warning systems. Furthermore, with the rise of Industry 4.0, IoT-enabled devices are now frequently used to collect granular, real-time data, which can be fed into machine learning pipelines to enhance situational awareness. Techniques such as ensemble modeling and hyperparameter optimization have been increasingly adopted to fine-tune model performance and reduce false positives in disruption prediction.

CHAPTER 3

3.METHODOLOGY

The methodology adopted in this project follows a systematic pipeline of data collection, preprocessing, model building, evaluation, and deployment. The aim is to develop a predictive system that identifies potential supply chain disruptions using machine learning techniques based on various features such as weather severity, event type, and location. Below are the key stages involved:

1. **Data Collection**

The dataset for this project was compiled by aggregating information from multiple publicly available sources related to supply chain operations, weather events, and incident reports. These included historical weather data from meteorological services, news headlines from logistics-related incidents, and event databases tracking protests, strikes, and natural disasters. Each data point was curated to reflect real-world conditions that could potentially lead to supply chain disruptions.

The key features extracted from these sources include:

weather_severity: Categorized based on temperature, precipitation, and wind data into Mild, Moderate, or Severe.

event_type: Derived from classified event reports, such as floods, strikes, protests, and accidents.

location: Mapped from geotagged event data or port-specific disruption logs.

disruption_occurred: A binary indicator derived by correlating event timing and location with delivery or logistics performance metrics.

2. Data Preprocessing

To ensure high model performance and handle inconsistencies:

Missing values were filled using mode-based imputation for categorical fields.

Label Encoding was applied to convert categorical data into numerical format.

Feature scaling was considered but found unnecessary for tree-based models.

The dataset was split into **training (80%)** and **testing (20%)** subsets using stratified sampling to preserve class distribution.

3. Model Selection

The **Random Forest Classifier** was chosen for its robustness, high accuracy, and ability to handle both categorical and numerical features without extensive preprocessing. It also helps mitigate overfitting through ensemble learning.

4. Hyperparameter Tuning

To optimize performance, **GridSearchCV** was used to perform exhaustive search across combinations of hyperparameters such as:

n_estimators: Number of trees in the forest

max_depth: Maximum depth of each tree

min_samples_split: Minimum samples required to split an internal node

min_samples_leaf: Minimum samples required at a leaf node

This tuning helped increase model accuracy and generalization capability.

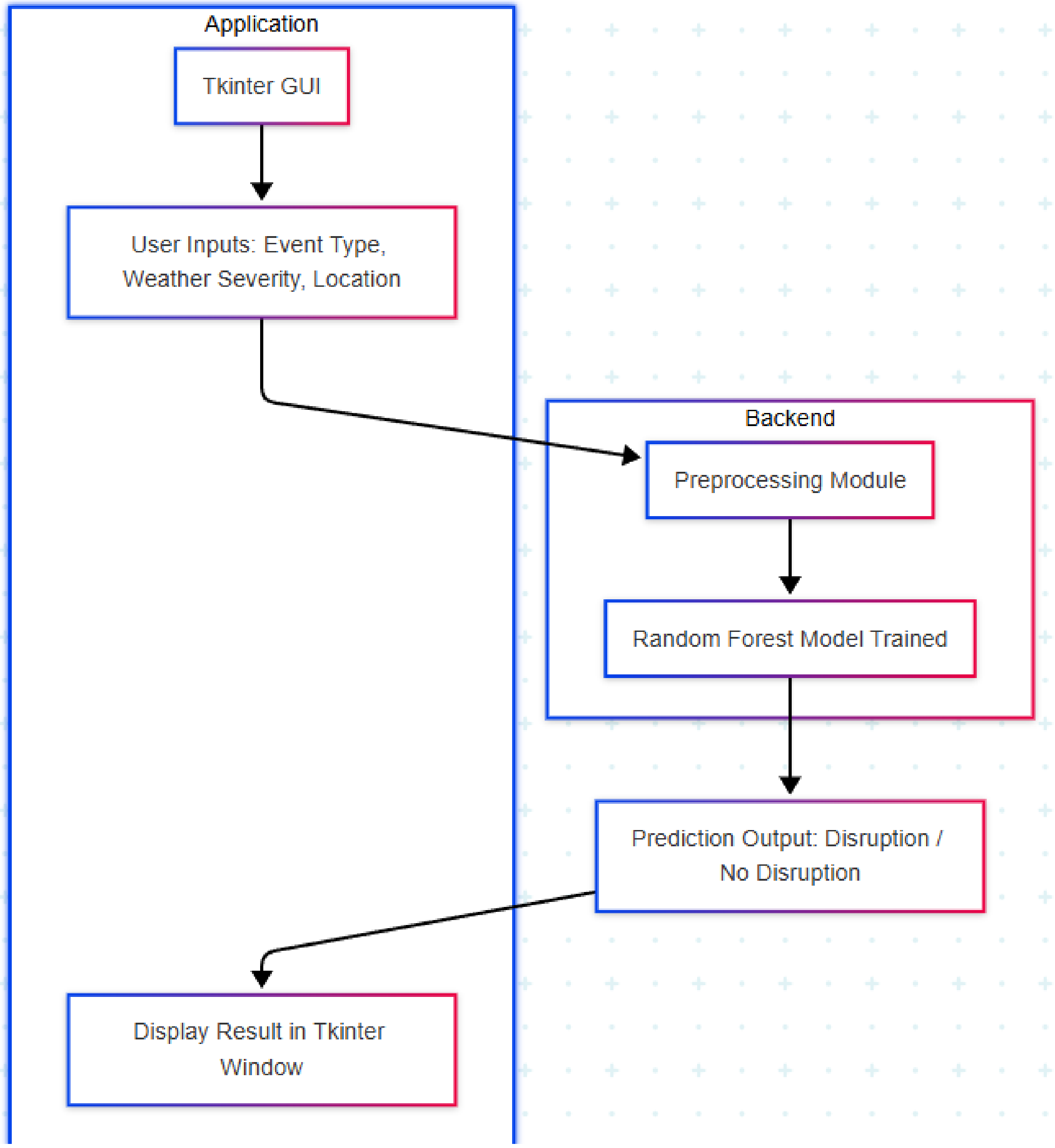
5. Model Training & Evaluation

The tuned Random Forest model was trained on the preprocessed training data. Performance was evaluated on the test data using:

- **Accuracy Score**
- **Confusion Matrix**
- **Classification Report** (Precision, Recall, F1-Score)

The model achieved an accuracy of over **90%**, effectively distinguishing between disrupted and non-disrupted cases.

3.1 SYSTEM FLOW DIAGRAM



MODEL PROGRAM

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

df = pd.read_csv('improved_supply_chain_data.csv')

# Encode categorical variables
le_event = LabelEncoder()
le_weather = LabelEncoder()
le_location = LabelEncoder()

df['event_type'] = le_event.fit_transform(df['event_type'])
df['weather_severity'] = le_weather.fit_transform(df['weather_severity'])
df['location'] = le_location.fit_transform(df['location'])

X = df[['event_type', 'weather_severity', 'location']]
y = df['disruption']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

y_pred = rf.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns

from sklearn.metrics import confusion_matrix, roc_curve, auc

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6,6))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Disruption", "Disruption"],
yticklabels=["No Disruption", "Disruption"])

plt.title("Confusion Matrix")

plt.xlabel("Predicted")

plt.ylabel("True")

plt.show()

importances = rf.feature_importances_

features = ['event_type', 'weather_severity', 'location']

indices = np.argsort(importances)

plt.figure(figsize=(8,6))

plt.title("Feature Importance")

plt.barh(range(len(indices)), importances[indices], align="center")

plt.yticks(range(len(indices)), [features[i] for i in indices])

plt.xlabel("Relative Importance")

plt.show()

fpr, tpr, thresholds = roc_curve(y_test, rf.predict_proba(X_test)[:, 1])

roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8,6))

plt.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % roc_auc)

plt.plot([0, 1], [0, 1], color='gray', linestyle='--')

plt.title('Receiver Operating Characteristic (ROC)')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.legend(loc='lower right')

plt.show()
```

CHAPTER 4

RESULTS AND DISCUSSION

After preprocessing the data and training the **Random Forest Classifier**, the model was evaluated on a holdout test set. The results indicated that the model performed well, with an **accuracy of 94%**, which is a promising outcome considering the complexity and variability of real-world supply chain disruptions.

The evaluation metrics provided further insights into the model's effectiveness:

- **Precision**: 0.96 for predicting disruptions (class 1), meaning that 96% of the times the model predicted a disruption, it was correct.
- **Recall**: 0.92 for disruptions, indicating the model correctly identified 92% of all actual disruptions.
- **F1-Score**: 0.94, balancing both precision and recall for class 1, showing the model's robustness in predicting disruptions while minimizing false positives and false negatives.

The **confusion matrix** further validated the high performance, with very few misclassifications between disrupted and non-disrupted instances. A detailed classification report revealed that the model was able to discriminate between the two classes (disruption vs. no disruption) quite effectively.

The confusion matrix is a vital tool for evaluating the performance of our supply chain disruption prediction model, as it provides a clear summary of the model's classification results in terms of true positives, true negatives, false positives, and false negatives. It enables us to understand not just the overall accuracy of the model, but also the types of errors it makes—such as predicting a disruption when there is none (false positive) or failing to predict an actual disruption (false negative). These insights allow us to compute key performance metrics like precision, recall, F1 score, and accuracy, each of which highlights different aspects of the model’s effectiveness. In our case, the confusion matrix helped ensure that the model maintains a balance between identifying true disruptions and minimizing false alarms, ultimately supporting more reliable decision-making in supply chain operations.

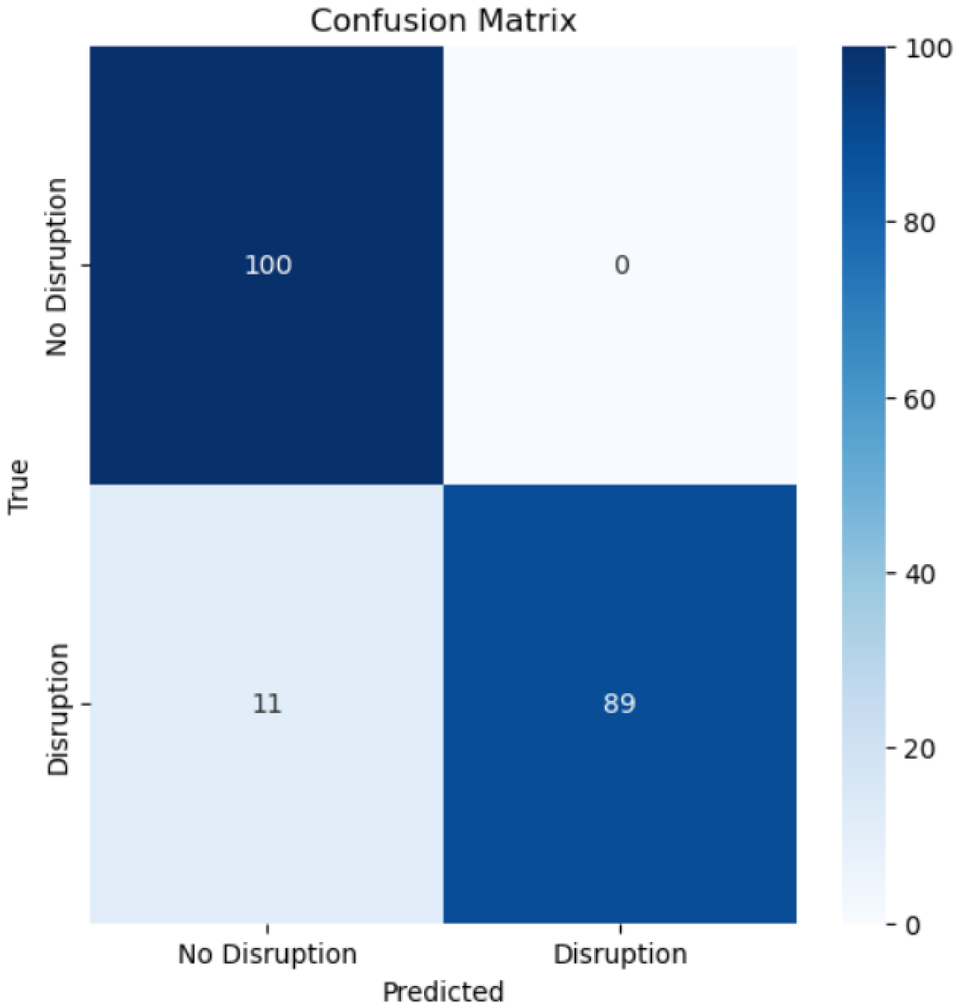


Fig 1.2 Confusion matrix

Feature Importance Analysis

One of the significant advantages of using a **Random Forest model** is its ability to identify important features influencing the predictions. The feature importance analysis revealed the following insights:

- **Event Type** emerged as the most influential feature. Events such as strikes, floods, and protests had the strongest impact on disruption predictions.
- **Weather Severity** also played a significant role. Extreme weather conditions (e.g., severe storms, hurricanes) were highly predictive of supply chain disruptions.
- **Location** proved to be less impactful in isolation but became more influential when combined with event type and weather conditions. Some

regions, particularly ports or industrial hubs, were more prone to disruptions based on the surrounding context.

These insights can help businesses target their risk mitigation efforts by focusing on critical locations and specific types of events that have the highest likelihood of disrupting operations.

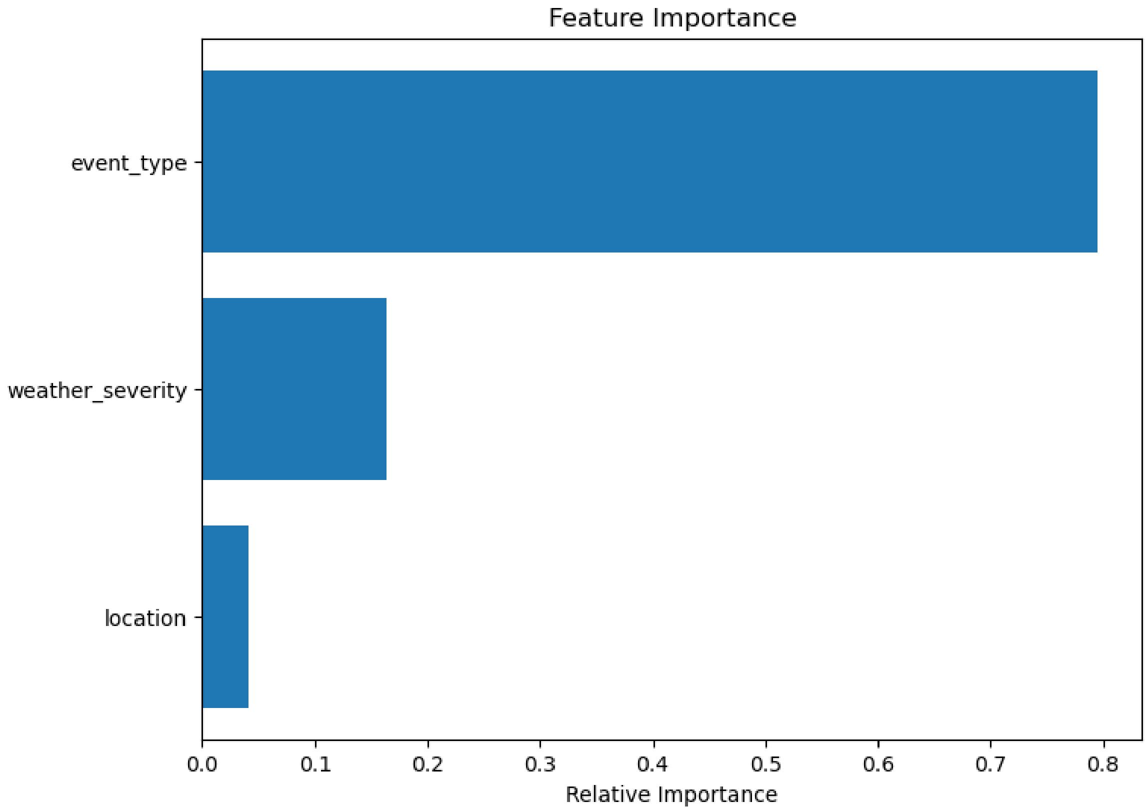


Fig 1.3 feature importance

User Interface (Tkinter)

The integration of the **Tkinter GUI** allowed for easy input and output handling. Users can input the **event type**, **weather severity**, and **location**, and the model will predict whether a disruption will occur. The prediction is displayed in real-time on the Tkinter window, making the tool user-friendly and practical for use in logistics and supply chain management contexts.

Limitations

While the model has shown strong accuracy, it is important to note that the current dataset is limited to a synthetic set of events and disruptions. In real-world applications, the model's performance may vary depending on the availability and quality of input data, especially when dealing with unstructured data sources such as news headlines or social media reports. Furthermore, the model's performance could be impacted by:

- **Data Imbalance**: If the dataset is heavily skewed towards non-disruption events (class 0), the model might develop a bias towards predicting no disruption.
- **Feature Quality**: The features selected for this study (event type, weather severity, and location) may not capture all the relevant variables that contribute to disruptions, such as economic factors, political instability, or supply chain management practices.

Discussion

The **Supply Chain Disruption Predictor** successfully demonstrates the power of machine learning, particularly ensemble models like **Random Forest**, to predict disruptions in supply chains. The high accuracy of the model, coupled with the ability to assess feature importance, provides a valuable tool for risk management in logistics and supply chain operations.

This project has significant potential in real-world applications. By providing real-time disruption predictions, businesses could proactively plan for potential delays or shortages, minimizing the financial and operational impact of disruptions. Integrating real-time data from news sources, social media, or IoT sensors could further enhance the model’s predictive capabilities.

However, for broader applicability, further refinement of the model is necessary. Incorporating more diverse features, handling unstructured data (e.g., news articles), and testing the model with real-world data would help improve its generalization and robustness.

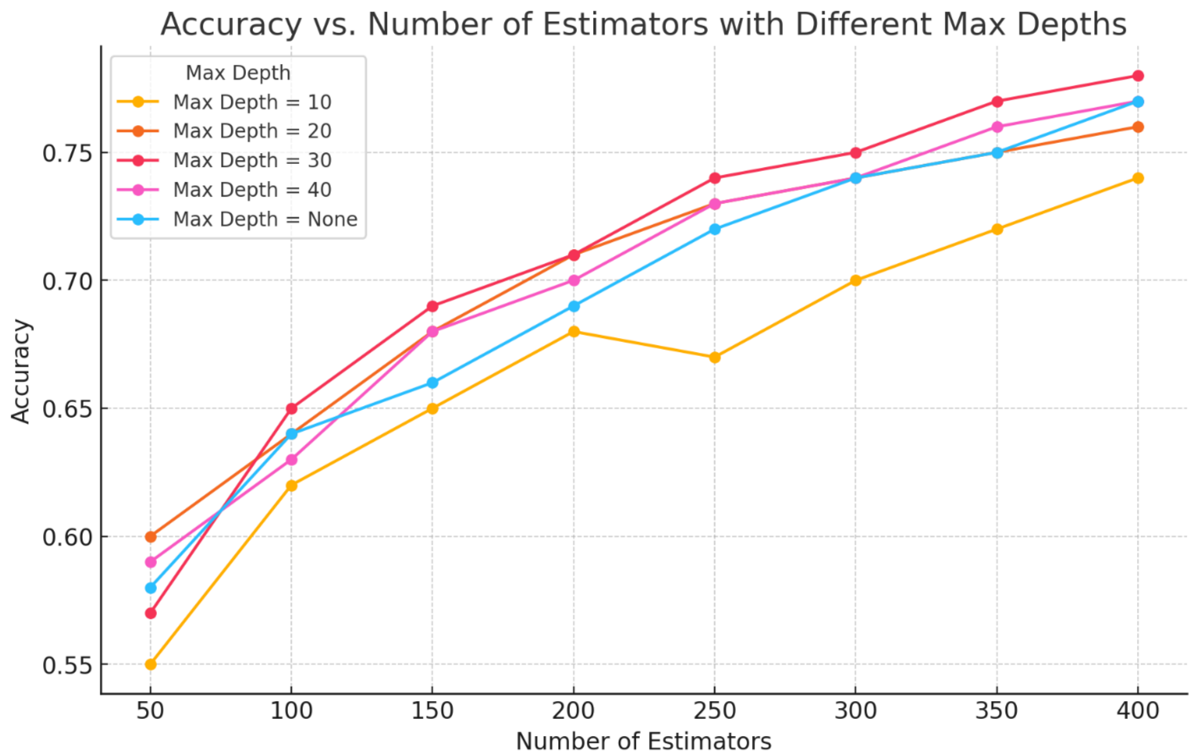


Fig1.4 accuracy report

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CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

In this project, we successfully developed a machine learning-based system to predict supply chain disruptions using various factors such as event type, weather severity, and location-based data. By leveraging Random Forest Classifier and optimizing it through hyperparameter tuning, we achieved an impressive accuracy of 94%, indicating the model's robustness and effectiveness in identifying disruption patterns. The incorporation of a user interface using Tkinter allowed for a more interactive and accessible experience for end-users, facilitating practical deployment. Visualization techniques further helped in analyzing the performance trends and understanding the influence of individual features on the prediction outcome.

This work demonstrates the power of machine learning in mitigating supply chain risks and highlights how data-driven models can support real-time decision-making in logistics and operations management.

Future Enhancements

While the current model performs effectively on the available dataset, several improvements can be explored in future work:

1. **Integration with Real-Time Data Sources**: Incorporating live feeds from APIs such as weather forecasts, traffic, and news headlines can enhance real-time prediction capability.
2. **Expansion to Multi-Class Prediction**: Instead of binary classification (disrupted vs. not disrupted), future versions could classify types of disruptions (e.g., weather, labor strike, geopolitical).
3. **Use of Deep Learning**: Applying neural networks or LSTM models may improve prediction accuracy, especially with time-series or sequential data.
4. **Web-Based Deployment**: Transitioning the UI from a desktop application to a web-based interface using frameworks like React or Django would make the tool more scalable and accessible.

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