RAJALAKSHMI ENGINEERING COLLEGE
An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chennai

25 years OF ACADEMIC EXCELLENCE

Department of Computer Science and Engineering

SUPPLY CHAIN DISRUPTION PREDICTOR

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Problem Statement and Motivation

- Global supply chains are increasingly exposed to disruptions from natural disasters, labor strikes, political instability, and logistics failures.
- Traditional systems are reactive, lack predictive capability, and fail to integrate real-time data. This results in delayed responses, financial losses, and reduced efficiency.
- Global supply chains face increasing risks from events like strikes and extreme weather. Traditional systems react too late, causing major losses. This project uses machine learning to predict disruptions in advance, enabling faster, data-driven responses

Existing System

Existing supply chain risk management systems primarily rely on rule-based approaches and historical data to monitor disruptions. These systems are typically reactive, issuing alerts only after a disruption has occurred. They often lack integration of real-time, multi-source data such as political news, labor unrest, or weather conditions, limiting their effectiveness in dynamic environments. Moreover, traditional statistical models used in these systems struggle to capture complex, non-linear patterns in disruption factors, resulting in lower prediction accuracy. Due to these limitations, businesses face delayed responses and financial losses, highlighting the need for more intelligent, predictive systems driven by machine learning

Objectives

- Develop a machine learning-based system to predict supply chain disruptions using structured event data.
- Integrate real-time and historical data sources like weather, strikes, and political events for accurate prediction.
- Implement a user-friendly interface using Tkinter to allow users to input data and receive instant predictions.
- Enhance prediction accuracy and model reliability through Random Forest algorithm and performance evaluation.

Abstract

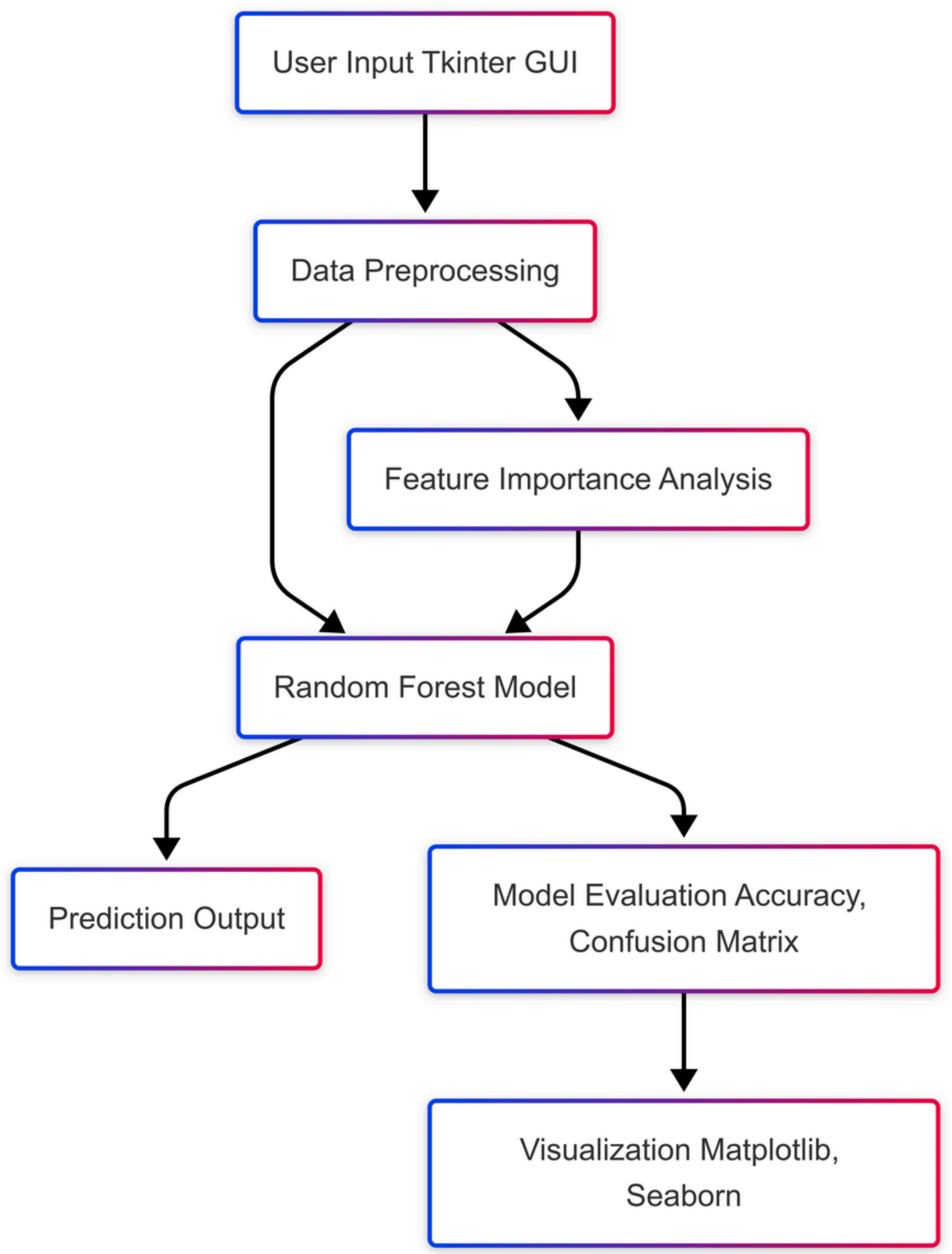
Supply Chain Disruption Predictor (SCDP) uses machine learning to proactively forecast supply chain disruptions. Unlike traditional reactive systems, it leverages a Random Forest Classifier trained on structured event data like weather severity, strikes, and location.

Visualization tools such as Matplotlib and Seaborn help analyze performance, and the model achieved over 90% accuracy through hyperparameter tuning, showing strong potential to enhance supply chain resilience.

Proposed System

- Machine Learning-Based Prediction: Utilizes a Random Forest Classifier to predict potential supply chain disruptions based on event-driven input features like weather severity, strikes, and political instability.
- Multi-Layered Architecture: The system is modular with components for data preprocessing, model training, prediction, user interaction (Tkinter GUI), and result visualization.
- Real-Time User Interaction: A user-friendly interface allows real-time input of disruption indicators and instant feedback on potential risk prediction.
- Enhanced Accuracy and Adaptability: Incorporates hyperparameter tuning and feature importance analysis to improve prediction performance and adapt to changing data trends.

System Architecture



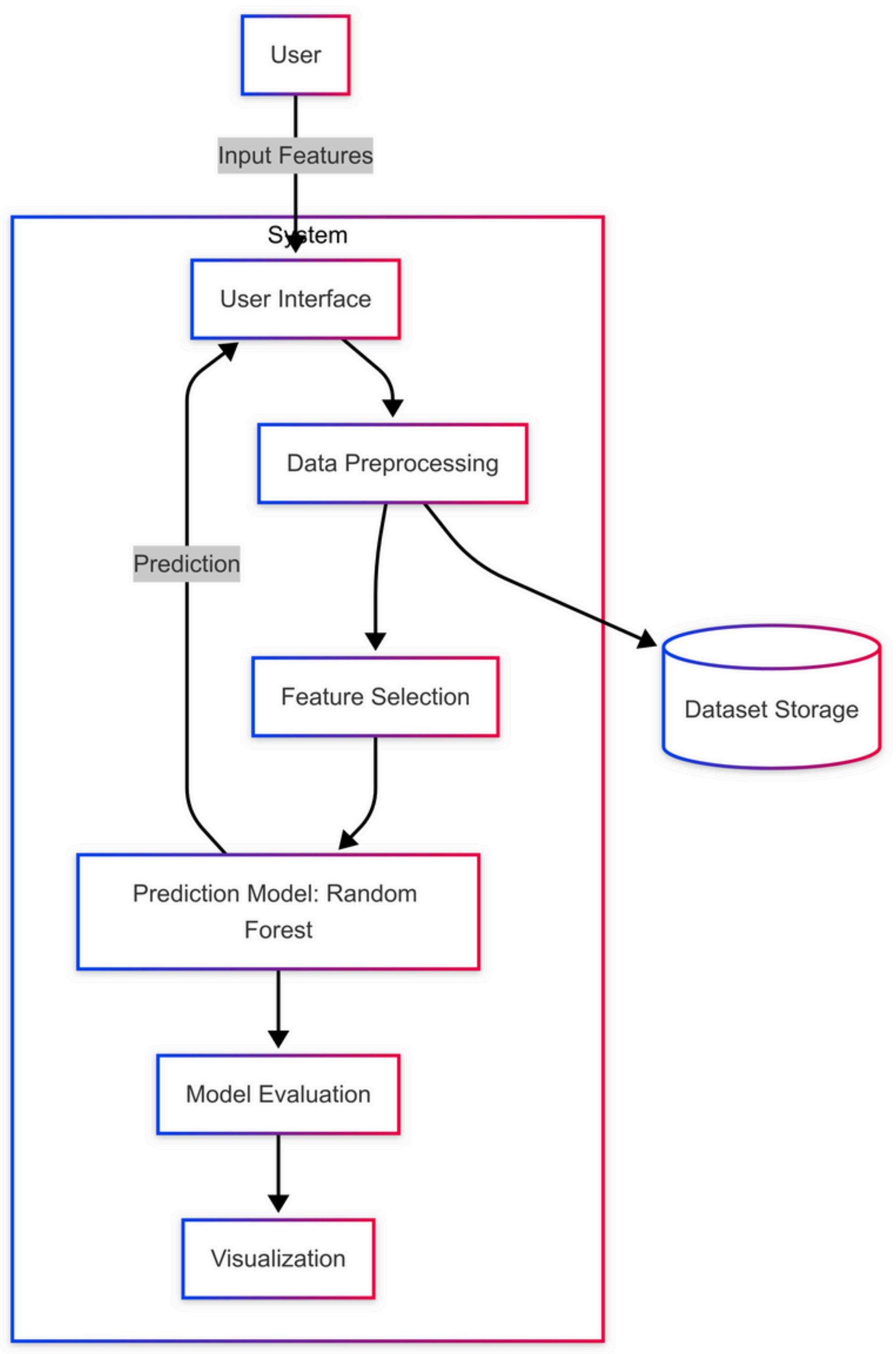
The system architecture is modular, consisting of layers for user interaction, data preprocessing, machine learning, and result visualization. Users input data through a Tkinter-based GUI, which is cleaned and transformed before being fed into a Random Forest Classifier. This model processes the inputs to predict potential supply chain disruptions.

The results, along with performance metrics such as accuracy and confusion matrix, are then visualized using libraries like Matplotlib and Seaborn to assist in model evaluation and interpretation.

List of Modules

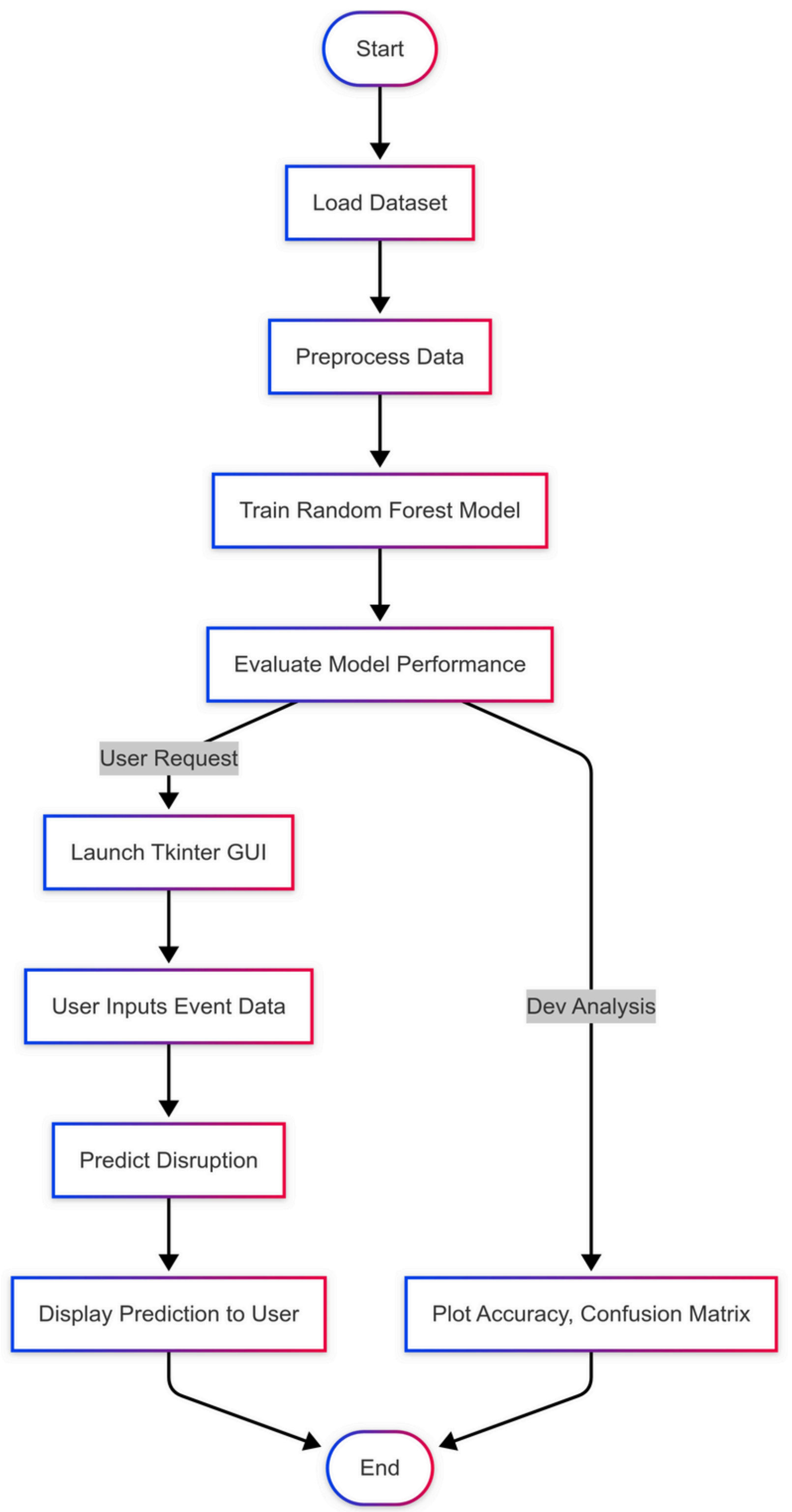
- **User Interface Module**: Built using Tkinter, it collects input data and displays predictions to the user.
- **Data Preprocessing Module**: Cleans, transforms, and prepares the input data for the model.
- **Feature Selection Module**: Identifies the most relevant features affecting supply chain disruptions.
- **Prediction Module**: Uses a trained Random Forest Classifier to predict disruption risks.
- **Model Evaluation Module**: Assesses the model's performance using metrics like accuracy and confusion matrix.
- **Visualization Module**: Uses Matplotlib and Seaborn to visualize performance metrics and feature importance.

DFD and Activity Diagram



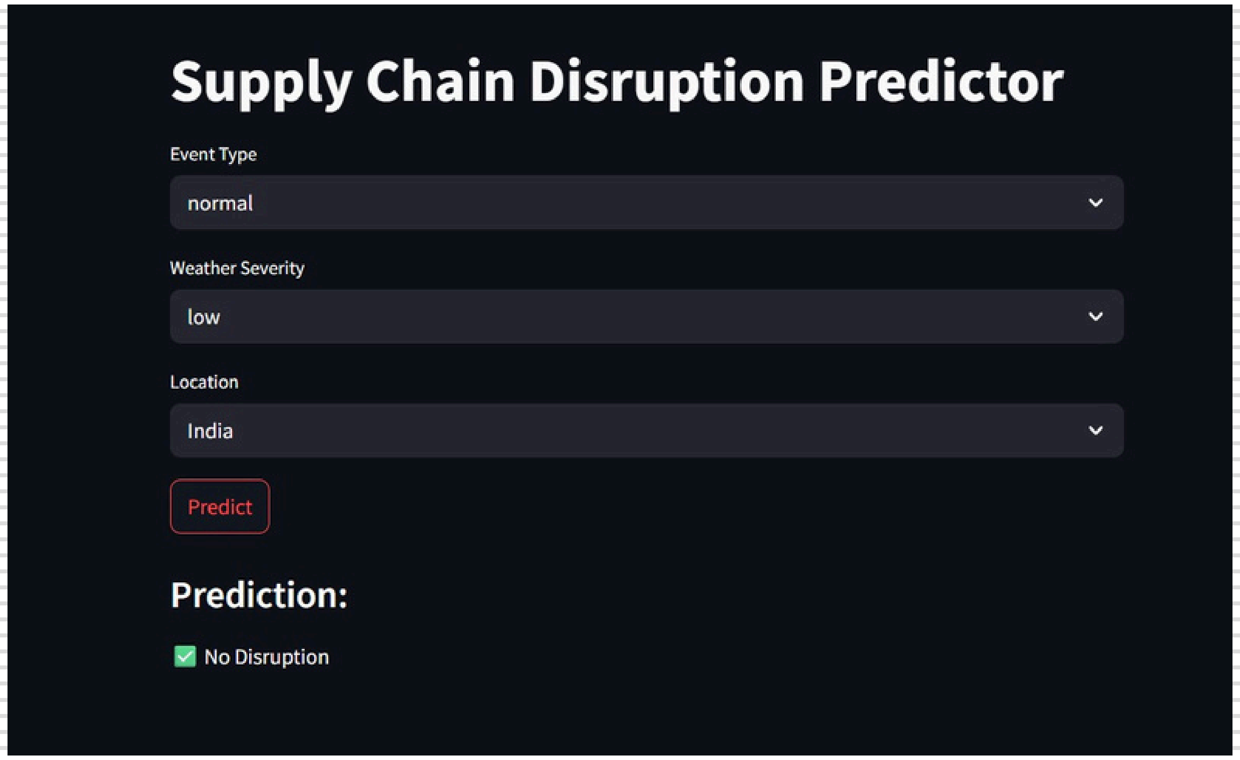
- User: Provides input (like weather data, strike reports, etc.) via the user interface.
- Input Module: Takes raw data and sends it to the Preprocessing module.
- Preprocessing Module: Cleans and transforms the input into a structured format.
- ML Model (Random Forest Classifier): Receives preprocessed data and performs prediction.
- Prediction Result: Sent back to the user via the GUI.
- Data Store: Stores historical inputs, model results, and logs for further training or analysis

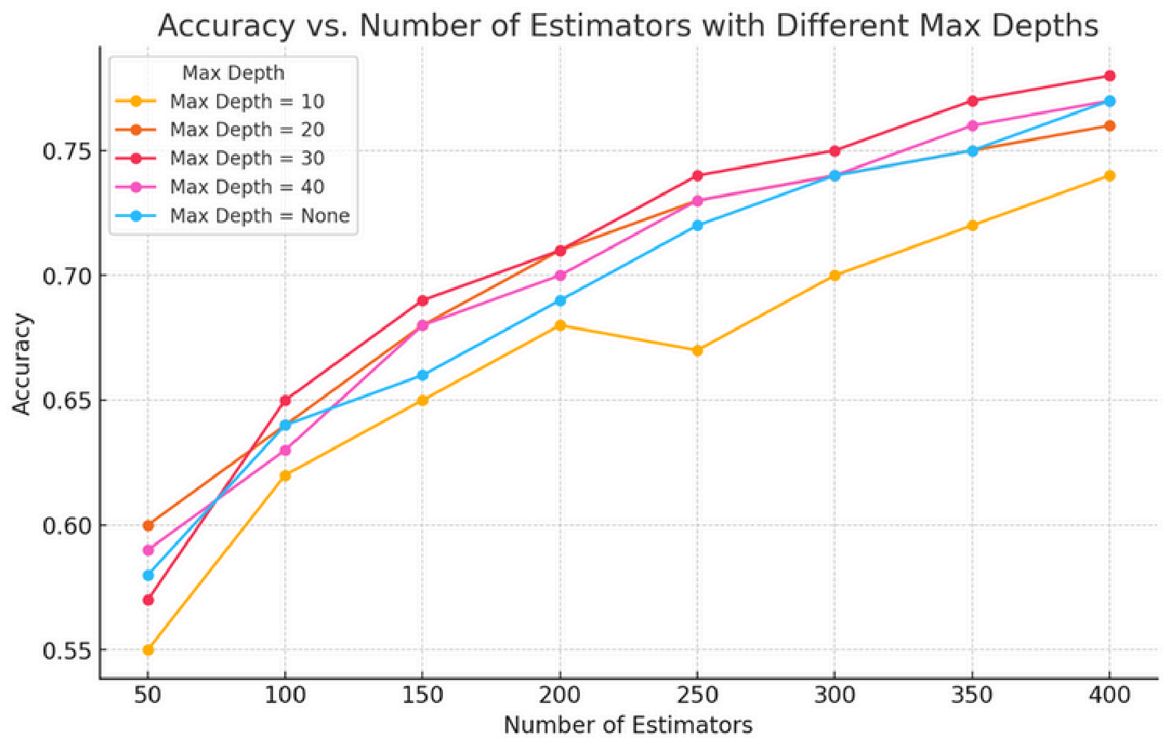
DFD and Activity Diagram



- The process starts with loading and preprocessing the dataset.
- Then, the Random Forest model is trained.
- After evaluation, the system either:
- Visualizes performance metrics like accuracy/confusion matrix, or
- Launches the Tkinter GUI for user interaction.
- When a user enters new data, the model predicts disruption, and the result is shown.
- The flow ends after displaying or storing results.

Implementation & Results of Module





The Supply Chain Disruption Predictor achieved an accuracy of over 90% using a Random Forest Classifier. The model effectively identified potential disruptions based on inputs like weather conditions, strikes, and location data. Performance was evaluated through confusion matrix analysis and visualized using accuracy and feature importance plots, confirming the reliability and predictive strength of the system

Conclusion & Future Work

The Supply Chain Disruption Predictor effectively leverages machine learning, particularly Random Forest, to forecast disruptions based on real-world event data. It provides timely, data-driven insights that help businesses minimize delays and financial losses

Future Scope:
Future enhancements may include integrating real-time data streams (e.g., APIs for weather or news), expanding to other ML models like XGBoost, and deploying the system as a scalable web-based dashboard for enterprise use.

References

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- [2] F. A. Nia, R. Tavakkoli-Moghaddam, and M. Rabbani, "A review of machine learning applications in supply chain management," Computers & Industrial Engineering, vol. 164, 2022.
- [3] A. Shukla, S. Garg, and J. Agarwal, "Supply chain risk mitigation using predictive analytics," Procedia Computer Science, vol. 132, pp. 927–935, 2018.

Thank You