AI SUPPLY CHAIN MANAGEMENT

INTERDISCIPLINARY PROJECT

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
Specialization in Artificial Intelligence & Machine Learning

by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
CATEGORY - 1 UNIVERSITY BY UGC
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APRIL - 2025

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Interdisciplinary Project Report is the bonafide work of **Mr. SANJAY (Reg no: 42611123)** who carried out the Project entitled **"AI SUPPLY CHAIN MANAGEMENT"** under my supervision from January 2025 to April 2025.

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26/4/25

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DECLARATION

I, **SANJAY (Reg no: 42611123)**, hereby declare that the Interdisciplinary Project Report entitled **"AI SUPPLY CHAIN MANAGEMENT"** done by me under the guidance of **Dr. R. SATHYA BAMA, M.E., Ph.D.,** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering with Specialization in Artificial Intelligence & Machine Learning**.

DATE: 26/04/2025

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COURSE CERTIFICATE

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CERTIFICATE FOR INTERNSHIP

TO WHOMSOEVER IT MAY CONCERN

This is to Certify that **Sanjay J (Reg No: 42611123)** student of Sathyabama Institute of Science and Technology, B.E CSE AIML, has successfully completed the Internship at Hackwit Technologies.

During the internship **Sanjay J** has closely worked as a part of the **Augmented Reality & Virtual Reality** by carrying out the project entitled **"AR Furniture App".**

He demonstrated good developing and learning skill with self-motivated attitude to learn new things. His contribution to implement the Artificial Intelligence was good. We wish him all the best for his future endeavors.

Best Regards,

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ABSTRACT

In the rapidly evolving landscape of global commerce, efficient and intelligent Supply Chain Management (SCM) has become essential for businesses to remain competitive, resilient, and responsive to market demands. This project presents a comprehensive AI-powered SCM solution that leverages the capabilities of Deep Learning, particularly Long Short-Term Memory (LSTM) neural networks, to enhance demand forecasting and inventory planning. Developed using TensorFlow, the system is designed to process historical supply chain data and identify complex patterns in sequential datasets to generate accurate time-series forecasts. These forecasts assist businesses in making data-driven decisions regarding restocking quantities, thereby minimizing the risks of overstocking or stockouts. The LSTM model, trained on various supply chain features such as product type, price, availability, customer demographics, shipping costs, lead times, and production volumes, captures temporal dependencies and delivers robust predictions that can significantly improve operational efficiency.

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CHAPTER 1

INTRODUCTION

In the modern era of digital transformation and globalization, businesses are facing unprecedented challenges and opportunities within their operational landscapes. Among these, Supply Chain Management (SCM) has emerged as one of the most crucial pillars of enterprise success. SCM involves the coordination of various interconnected processes including procurement of raw materials, production scheduling, inventory control, logistics, distribution, and final delivery to the customer. With increasing demand variability, shorter product life cycles, global sourcing, and heightened customer expectations, traditional methods of managing supply chains have proven inadequate.

As a result, the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into supply chain operations has gained tremendous attention. These technologies bring intelligence and automation to decision-making processes that were previously handled manually or based on fixed rules. AI systems are capable of handling vast and complex datasets, learning patterns from historical data, and making accurate predictions. This ability is particularly valuable in supply chains, where timely and accurate forecasts can lead to significant reductions in costs, improvements in service levels, and better utilization of resources.

This project proposes a practical and deployable AI-based solution for supply chain demand forecasting and inventory optimization, using Deep Learning models, specifically Long Short-Term Memory (LSTM) networks. The goal is to predict future product demand based on historical data and various influencing factors such as lead times, shipping costs, production volumes, customer demographics, and product availability. These predictions help businesses determine the optimal quantity of stock to reorder, minimizing the risks of overstocking and stockouts.

Unlike traditional forecasting tools, which often use linear models or assumptions, LSTM models are designed to process sequential data and capture long-term dependencies. The integration of AI with intuitive design lowers the barrier for adoption in small and medium enterprisesThis makes them well-suited for time-series problems, which are common in supply chain datasets. The model is implemented using TensorFlow, one of the most powerful and flexible deep learning frameworks available today.

To ensure accessibility and user-friendliness, the system is deployed using the Flask web framework, with a frontend interface built using HTML and CSS. The user inputs are preprocessed using a saved data transformation pipeline and passed to the LSTM model to generate real-time predictions. This fusion of AI and web technologies not only makes the system intelligent but also interactive, scalable, and ready for real-world applications. It empowers supply chain managers and decision-makers with predictive insights, enabling them to respond to changes in demand proactively rather than reactively.

The global economy has experienced a dramatic shift over the past decade, driven by rapid advancements in technology, data availability, and automation. As a result, modern supply chains have become increasingly complex, interconnected, and data-intensive. This complexity brings new challenges, such as unpredictable demand patterns, production delays, transportation bottlenecks, and rising costs. Traditional supply chain management techniques, which often rely on historical trends, manual analysis, and static rule-based systems, are no longer sufficient to handle the dynamic nature of global commerce. To remain competitive and responsive, organizations must adopt intelligent systems that are capable of understanding data patterns and making timely predictions. This is where Artificial Intelligence (AI) and Machine Learning (ML) offer significant advantages.

This project presents a real-world application of AI in the domain of Supply Chain Management (SCM) by developing a system capable of accurately forecasting demand and recommending restocking strategies. The system uses Long Short-Term Memory (LSTM) networks—a type of Recurrent Neural Network (RNN)—which are particularly suitable for sequential and time-series data. LSTM models overcome the limitations of traditional RNNs by effectively learning long-term dependencies in data. This enables the system to capture subtle temporal patterns and correlations that influence product demand, such as seasonality, lead time variations, and customer behavior shifts.

The LSTM model is implemented using TensorFlow, which provides robust capabilities for building and training deep learning models. The training data includes a wide variety of supply chain parameters such as product types, availability, production volumes, shipping carriers, lead times, manufacturing costs, inspection results, and more. The model learns how these variables interact and impact future demand, ultimately allowing it to predict the required quantity of items to be restocked at any given point in time. The integration of AI with intuitive design lowers the barrier for adoption in small and medium enterprises

To make this AI functionality accessible to users, the system is deployed using a lightweight Flask backend, which handles all input routing, preprocessing, and model inference operations. The frontend, built using HTML and CSS, offers a clean and simple interface for users to input data and instantly receive predictions. This full-stack integration ensures that the system is not only intelligent but also interactive, easy to use, and deployable in real-world environments.

The system also calculates the estimated cost of restocking, based on factors such as shipping charges and manufacturing costs, offering additional business value. These financial estimates are crucial for managers and supply planners to make strategic decisions that balance customer service levels with operational costs. By offering both predictive and prescriptive capabilities, the solution moves beyond basic forecasting and provides actionable insights for business optimization.

One of the most important aspects of this system is its scalability and adaptability. While this project serves as a prototype, the architecture supports future expansion, including real-time data integration, database storage for historical tracking, dashboard analytics, multi-product forecasting, alert systems for low inventory, and potential integration with Enterprise Resource Planning (ERP) software. This makes it a versatile tool that can evolve alongside the business needs of various sectors, including retail, manufacturing, healthcare, agriculture, and logistics.

This overview encapsulates the motivation, design approach, technical foundation, and business relevance of the project. By aligning deep learning with user-friendly web technologies, the system empowers supply chain professionals to make informed, data-driven decisions. It reflects the transformative impact of AI in operations management and showcases a forward-thinking approach to addressing real-world supply chain challenges.The success of this project also opens doors for future enhancements like multi-product forecasting, live data streaming, and cloud-based deployment for wider scalability.With continuous refinement, the system has the potential to evolve into a comprehensive AI solution for end-to-end supply chain automation.Its lightweight design ensures easy deployment across devices and platforms without compromising performance.Additionally, the modular structure supports seamless updates and third-party integrations, enabling long-term flexibility. Overall, the system lays a strong foundation for the next generation of intelligent, automated supply chain tools.The integration of AI with intuitive design lowers the barrier for adoption in small and medium enterprises. This project represents a practical and scalable approach to digital transformation in supply chain ecosystems.

CHAPTER 2

LITERATURE REVIEW

2.1 REVIEW ON EXISTING SYSTEM

Supply Chain Management (SCM) is a complex and dynamic field that deals with the coordination of all activities involved in the procurement, production, and distribution of goods and services. With the rapid advancement of digital technologies and the increasing availability of data, the traditional approaches to managing supply chains are being replaced by intelligent, data-driven systems. These modern systems leverage Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques to enhance forecasting, optimize inventory, reduce operational risks, and improve customer satisfaction.

In the traditional supply chain ecosystem, demand forecasting is one of the most critical yet challenging aspects. Conventional statistical methods such as Moving Averages, ARIMA (Auto-Regressive Integrated Moving Average), and Exponential Smoothing have long been used to predict future demand based on historical data. While these models work well in stable environments, they often fall short in capturing non-linear trends, sudden fluctuations, and multi-factor influences that characterize real-world supply chains. As businesses grow in scale and complexity, there is a need for models that can learn from large volumes of data and recognize hidden patterns across multiple variables.

This has led to a shift towards AI-based forecasting models, particularly those using Deep Learning architectures. Among these, Long Short-Term Memory (LSTM) networks have shown exceptional performance in time-series forecasting due to their ability to maintain long-term dependencies in sequential data. LSTM networks are a specialized form of Recurrent Neural Networks (RNNs) designed to overcome the vanishing gradient problem, enabling them to remember important data patterns over long sequences. This is particularly useful in supply chains where demand is influenced by historical sales data, seasonality, promotional events, supplier performance, shipping delays, and other time-bound factors.

LSTM models are capable of processing multivariate inputs, which allows them to consider multiple influencing factors simultaneously. For example, in a retail supply chain, an LSTM model can analyze data such as customer demographics, product types, stock availability, pricing, and shipping lead times to predict future demand with high accuracy. Moreover, when

implemented with robust frameworks like TensorFlow, these models offer scalability, flexibility, and ease of deployment, making them suitable for real-world enterprise applications.

The practical deployment of AI models in supply chains also relies heavily on integration with accessible platforms. This is where web technologies like Flask become instrumental. Flask is a lightweight Python-based web framework that allows for the seamless integration of backend AI models with frontend web interfaces. It provides a simple, flexible environment to handle user inputs, preprocess data, trigger model predictions, and return results in real-time. When paired with user-friendly frontend technologies like HTML and CSS, the system becomes not only intelligent but also accessible to non-technical users such as inventory managers, logistics coordinators, and business analysts.

The use of AI in SCM is not just limited to demand forecasting. AI models are increasingly being used in other aspects such as predictive maintenance, route optimization, supplier risk analysis, warehouse automation, and dynamic pricing. However, demand forecasting remains one of the most impactful use cases, as it directly affects inventory levels, production planning, customer service, and overall profitability. By accurately predicting future demand, companies can reduce overstocking, avoid stockouts, lower holding costs, and improve fulfillment rates.

Recent research has also explored the integration of AI systems with cloud computing and big data platforms, enabling real-time processing and global accessibility. This makes AI-powered SCM systems even more powerful, especially for multinational companies with complex supply networks. Furthermore, the modular nature of modern AI systems allows for continuous improvement through model retraining, feature expansion, and the addition of new data sources such as real-time sensor feeds, weather data, and social media trends. These advancements collectively contribute to building smarter, more resilient, and highly adaptive supply chains.

2.2 INFERENCES AND CHALLENGES IN EXISTING SYSTEM

Traditional supply chain management systems rely heavily on manual planning, basic statistical tools, or rule-based enterprise resource planning (ERP) systems to manage inventory, forecast demand, and make restocking decisions. While these systems have supported businesses for decades, they often fall short in today’s dynamic and data-intensive environments. One key inference from analyzing existing systems is their limited adaptability to sudden market changes, seasonal variations, and external disruptions such as supply shortages or logistic delays.

These systems typically depend on historical averages and fixed reorder levels, which do not account for complex dependencies or real-time supply chain variables.

A major challenge in existing systems is the inability to leverage multi-dimensional data. Inputs such as customer demographics, transportation modes, manufacturing lead times, and defect rates are often siloed or ignored entirely. As a result, the forecasts they generate lack contextual accuracy and often lead to overstocking or stockouts. Additionally, conventional methods do not accommodate time-series forecasting with memory-based learning, which is essential in predicting patterns and trends in inventory demand across time.

Another significant limitation is the lack of intelligent automation. Most existing systems still require manual intervention for stock adjustments, cost evaluation, and supplier coordination. This manual dependency not only increases the workload but also introduces human error and decision delays. Furthermore, existing systems often lack scalability and customization. Adapting them to different product categories, markets, or business sizes can be complex and cost-intensive. They are rarely modular, making it difficult to implement upgrades or integrate AI components without overhauling the entire system.

Moreover, traditional systems often lack integration with external data sources such as weather conditions, market trends, and social media signals, which can significantly influence consumer demand. Without these insights, forecasting models remain reactive rather than proactive. Cybersecurity is another overlooked concern in many outdated platforms, leaving sensitive supply chain data vulnerable to breaches. In today's global supply networks, where multiple vendors and logistics providers are involved, real-time collaboration is essential—but most legacy systems operate in isolation. Additionally, there is minimal support for mobile or remote access, limiting real-time decision-making for supply chain managers on the move. These limitations not only hinder innovation but also increase operational costs. The inability to scale rapidly during seasonal surges or crises like pandemics exposes systemic fragility. Thus, there is a strong need for systems that are not only intelligent but also adaptive, collaborative, and secure.

Lastly, many legacy systems do not support real-time data processing. This delay in information flow can cause businesses to react too late to changing demand or supply disruptions, negatively impacting profitability and customer satisfaction. These challenges clearly highlight the need for a modern, AI-driven, flexible, and user-centric supply chain management system that can forecast, recommend, and scale with ease.

CHAPTER 3

ANALYSIS AND DESIGN OF

PROPOSED SYSTEM

3.1 FUNCTIONAL REQUIREMENTS

Functional requirements define what the system should do—how it responds to user inputs, handles data, performs calculations, and delivers output. The AI-Based Supply Chain Management System is designed to provide a seamless user experience for forecasting product demand, generating restocking suggestions, and estimating costs. Below are the core functional requirements: The main objective of this project is to develop an AI-enabled Supply Chain Management system that improves demand forecasting and restocking decisions using Deep Learning techniques. By leveraging Long Short-Term Memory (LSTM) neural networks, the system can analyze historical supply chain data to predict future product demand with high accuracy. This allows businesses to make proactive inventory decisions, avoid overstocking or stockouts, and reduce operational costs. The model is developed using TensorFlow and deployed via a Flask-based web application, ensuring accessibility and usability for supply chain managers.

Intelligent Demand Forecasting

Develop a predictive model using Long Short-Term Memory (LSTM) neural networks to accurately forecast future product demand. This deep learning model will analyze historical supply chain data and identify time-dependent patterns, seasonality, and variations across multiple input features like stock levels, production volumes, lead times, and customer profiles. The system aims to reduce uncertainty in inventory planning and improve forecasting precision.

Real-Time Restocking Suggestions

Provide intelligent recommendations for restocking based on the predicted demand output. The system will calculate the difference between the forecasted demand and available stock, then suggest the quantity to reorder. This helps reduce excess inventory, avoid stockouts, and optimize procurement cycles, making the supply chain more cost-effective and responsive.These timely suggestions enable faster decision-making and improve overall supply chain agility.

Web-Based Accessibility

Design a lightweight, user-friendly web application using Flask (backend) and HTML/CSS (frontend) to make the system accessible to end-users like supply chain managers and inventory planners. Users will input product and shipping data through a web form and receive instant predictions and cost insights — all without needing any technical background.

Automated Cost Estimation

Incorporate a feature that calculates the estimated cost associated with restocking, including manufacturing and shipping expenses. This allows businesses to evaluate not just how much to reorder, but also the financial impact, helping in better budget planning and cost control.

Preprocessing and Model Integration

Use joblib-based preprocessing pipelines to clean and transform input data before passing it to the AI model. This ensures input compatibility and maintains consistency with the format used during training. The model and preprocessor will be integrated seamlessly into the backend, supporting quick, accurate predictions.

Deployment-Ready Architecture

Create a modular and scalable architecture that supports future enhancements like database integration, multi-product forecasting, and real-time analytics. The project is structured to be easily deployed on local servers or cloud platforms, enabling practical use in enterprise environments.

Scenario-Based Forecast Evaluation

Enable users to simulate multiple scenarios by altering input variables (e.g., lead time, shipping costs, demand trends) and observing how restocking needs change. This functionality supports strategic planning and improves response to unpredictable supply chain disruptions.It allows businesses to assess the impact of sudden market changes or supply delays before they occur. This proactive feature enhances agility and prepares organizations for uncertainty with data-backed decisions.Users can compare restocking outcomes across different what-if scenarios to identify the most cost-effective and risk-resilient options.

3.2 HARDWARE AND SOFTWARE REQUIREMENTS

HARDWARE REQUIREMENTS

- **CPU:** Multi-core processor (Intel i5/i7 or AMD Ryzen 5/7).
- **GPU:** 4–6 GB VRAM GPU (e.g., NVIDIA GTX 1050 Ti or higher).
- **RAM:** Minimum 8 GB, 16 GB recommended.
- **Storage:** 256 GB SSD or more.
- **Network:** High-speed internet (20 Mbps or above).
- **Display:** Full HD monitor (1920×1080).
- **Keyboard & Mouse:** Standard input devices.
- **Cooling System:** Basic cooling setup for stability.

SOFTWARE REQUIREMENTS

- **Python 3.8** - Programming language for model training & backend development
- **TensorFlow 2.x** – Deep learning library used to build and train the LSTM model
- **Flask** – Lightweight Python web framework for creating the backend API
- **Joblib** – For saving and loading the trained model and preprocessor pipeline
- **HTML5** – Structure and layout of the web interface
- **CSS3** – Styling and responsive design of the frontend
- **Jupyter Notebook** – For experimenting with datasets and model training
- **Pandas / NumPy** – Libraries for data manipulation and preprocessing
- **Scikit-learn** – Used for data transformation and feature engineering
- **Visual Studio Code / PyCharm** – Preferred code editors for development
- **Google Chrome / Firefox** – Browser for testing the web interface
- **Operating System:** Compatible with Windows 10, Linux (Ubuntu), or macOS
- **Localhost / WSGI Server (Gunicorn)** – For local deployment and testing
- **Postman (optional):** For testing API endpoints during development
- **Git** – Version control system for managing source code

CHAPTER 4

IMPLEMENTATION OF PROPOSED SYSTEM

4.1 SELECTED METHODOLOGY

The development of the AI-powered Supply Chain Management system is guided by a structured methodology, combining principles from data science workflows, machine learning lifecycle management, and agile web development. The process is segmented into clearly defined phases:

Requirement Analysis and Problem Understanding:

This phase involves understanding the challenges in traditional supply chain forecasting, such as demand uncertainty, delays, and overstocking. Stakeholder meetings and literature reviews helped define the project's goals—accurate demand forecasting and real-time restocking recommendations using AI models.

Data Collection and Preprocessing:

Historical sales data and supply chain attributes are gathered, cleaned, and transformed. Missing values are handled, time-series sequences are generated, and the data is scaled using a custom preprocessor saved as preprocessor.pkl for use during model inference.

Model Design and Development:

An LSTM-based deep learning model is chosen for its ability to retain long-term temporal dependencies. The model is built using Keras and trained on time-series data, with supply_chain_lstm_model.keras being the final output file used for deployment. Hyperparameters like epochs, batch size, and optimizer settings were tuned during experimentation. The model was evaluated using metrics like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to ensure accuracy. Its ability to handle multivariate inputs makes it highly effective for forecasting complex supply chain scenarios. The system is tested through unit testing, UI validation, and model accuracy checks (using RMSE and MAE). Thus the model is designed more efficiently.

4.2 ARCHITECTURE OF PROPOSED SYSTEM

System Architecture and Integration:

The system is modularized into the following:

App Module (app.py): Central Flask controller handling routes and API logic.

Preprocessing Module: Loads and applies the preprocessor.pkl to transform user inputs.

Model Module: Loads the .keras file and performs prediction.

UI Module: HTML templates (index.html, result.html) and static assets (CSS/JS) form the front end.

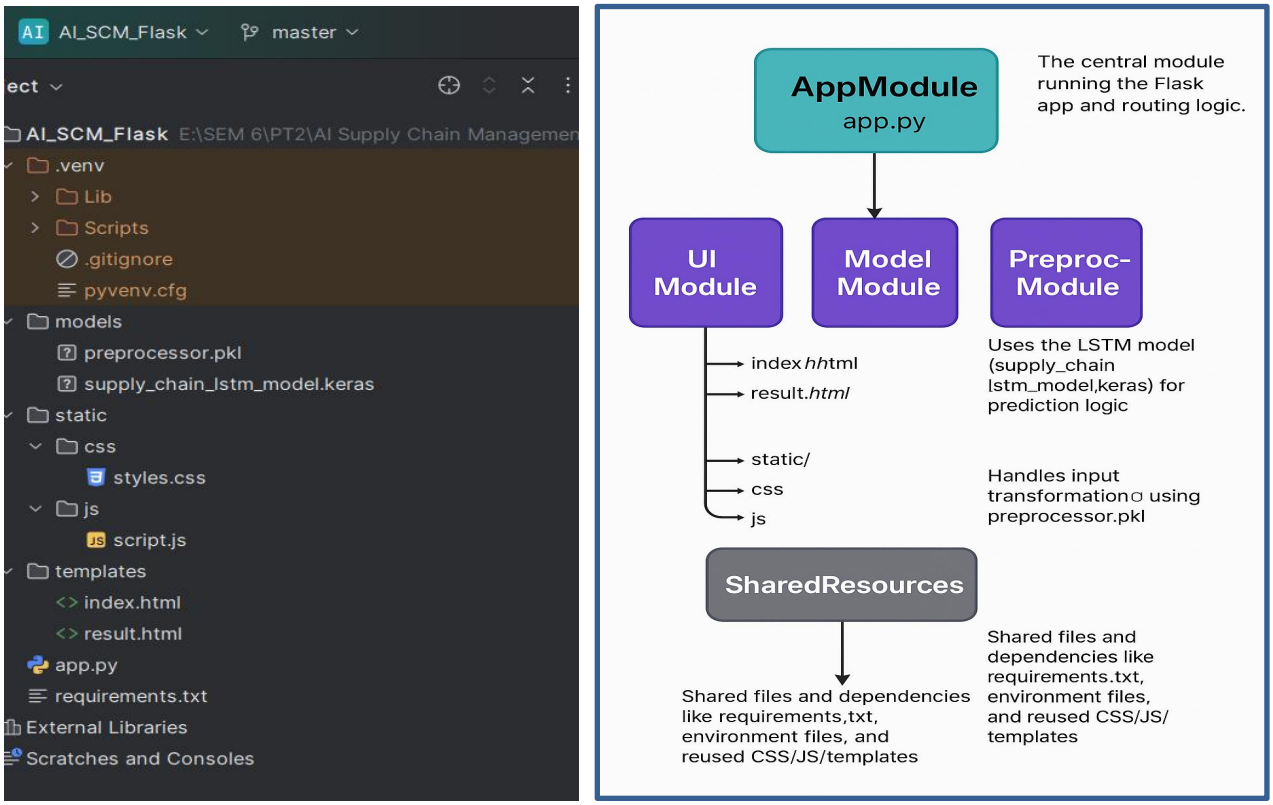

Fig 4.1.1. System Architecture & Directory Structure of SCM

The figure illustrates both the modular architecture and the corresponding directory structure of the Flask-based AI supply chain forecasting system. The architecture is centered around app.py, which handles routing logic and application execution. It connects three primary modules: UI Module, Model Module, and Preprocessing Module. The model is built using Keras and trained on time-series data, with supply_chain_lstm_model.keras being the final output file used for deployment.

The UI module contains HTML templates and static assets (CSS/JS), providing a user-friendly interface for data input and prediction results. The Model module loads the LSTM model (supply_chain_lstm_model.keras) to perform demand forecasting, while the Preprocessing module uses a pickled transformer (preprocessor.pkl) to process and scale inputs. Shared resources, such as requirements.txt and configuration files, are stored centrally to support maintainability. The front end is designed with HTML, CSS, and JavaScript, while Flask powers the backend, dynamically rendering prediction outputs. The system is tested through unit testing, UI validation, and model accuracy checks (using RMSE and MAE). It operates within a virtual Python environment and is easily deployable via Flask, with future readiness for Docker or cloud hosting. Iterative improvements guided by user feedback ensure the solution evolves with enhanced scalability, including support for multi-product predictions and real-time data integration. The directory structure mirrors this modular design, promoting organized development and efficient collaboration.

The AI-Based Supply Chain Management System operates based on key design and functional principles that ensure accurate forecasting, smooth user interaction, modularity, and scalability. These principles form the foundation of the system's architecture and guide its real-time AI functionality and web-based deployment.

Modular System Design

The application follows a modular design where each component (UI, preprocessing, model, cost calculation) is developed and maintained independently. This separation of concerns enables easier debugging, feature upgrades, and overall maintainability.Each module interacts through well-defined interfaces, ensuring smooth data flow between components.This architecture also facilitates team collaboration, allowing developers to work on different modules in parallel without conflicts.

AI-Driven Forecasting Logic

At its core, the system uses a trained LSTM model built with TensorFlow to perform time-series forecasting based on multiple supply chain features. The model is capable of understanding temporal patterns, enabling it to predict future product demand with high accuracy and minimal latency. It also supports multivariate inputs, allowing it to consider various influencing factors such as stock levels, lead times, and production volumes simultaneously for more reliable predictions.

Flask-Based API Communication

The frontend communicates with the backend using Flask routes that simulate RESTful behavior. When the user submits input via the form, Flask processes the request, preprocesses the data, invokes the LSTM model, and returns the prediction output for display on the result page.

Real-Time Input Processing

The system accepts user input through the web form and provides demand forecasts and restocking suggestions almost instantly. The backend leverages a serialized preprocessor.pkl to transform inputs on the fly, ensuring consistency with the training data structure.

User-Friendly Web Interface

The application is designed to be simple, responsive, and intuitive, allowing even non-technical users like supply chain managers to operate the system with ease. All results are rendered dynamically on result.html, improving interactivity and reducing wait times.

Input Validation and Error Handling

Before prediction, the system verifies that all required fields are filled and inputs are of valid types. Errors (e.g., missing fields or invalid values) are caught by the backend and displayed gracefully on the user interface, improving reliability.

Cost Estimation Engine

In addition to demand forecasting, the system calculates restocking costs using shipping and manufacturing inputs. This provides businesses with a financial estimate, supporting smarter procurement planning and budget allocation.

Deployment Readiness and Extensibility

The application is deployed in a local virtual environment and is structured to support future deployment to platforms like Docker or AWS. Its architecture also allows for scalable enhancements such as multi-product forecasting, real-time API integration, and dashboard visualizations. Its ability to handle multivariate inputs makes it highly effective for forecasting complex supply chain scenarios.

Performance Monitoring and Feedback

While currently running locally, the system includes logging and structured outputs to monitor model accuracy and prediction response times. Future feedback loops from real users can help in retraining the model and refining the user experience.

4.3 DESCRIPTION OF MODULES

The development of the AI-Based Supply Chain Management System follows a series of structured stages that contribute to the overall functionality, performance, and usability of the final application. Each stage is crucial to building an intelligent, scalable, and user-accessible platform capable of providing accurate demand forecasting and restocking suggestions.

Planning and Requirement Analysis:

In the initial phase, the need for intelligent demand forecasting and automated restocking was analyzed through literature reviews and problem scoping. The limitations of traditional forecasting methods in dynamic supply chains were identified, leading to the formulation of a clear objective: leveraging AI to improve inventory management. Stakeholder expectations and user requirements were documented to align technical development with practical business use. Benchmark studies were conducted to evaluate existing solutions and identify key areas of innovation.This phase served as the foundation for designing a solution that is both technically robust and user-centric.

Data Collection and Preprocessing:

Historical supply chain datasets were collected and cleaned for model training. This included handling missing values, encoding categorical variables, and scaling numerical features. The processed data was formatted for time-series input to match the requirements of LSTM networks. A serialized preprocessor (preprocessor.pkl) was created for consistent real-time input transformation during model deployment. Data normalization ensured that all input features were within a similar scale, preventing bias during model learning. Temporal features were engineered to capture seasonality and trends in the data, enhancing model performance.The final dataset was split into training and validation sets to evaluate model accuracy and prevent overfitting. Its ability to handle multivariate inputs makes it highly effective for forecasting complex supply chain scenarios.

Model Development:

A Long Short-Term Memory (LSTM) model was developed using TensorFlow and Keras. The model was trained on multivariate time-series data, learning to capture patterns like seasonality and supplier delays. Key hyperparameters such as epochs, learning rate, and batch size were tuned during experimentation. The trained model was exported as supply_chain_lstm_model.keras for deployment in the Flask application.

System Design and Integration:

The system was modularly designed with a clear separation of concerns. Flask handled backend logic, routing, and model integration, while HTML/CSS templates formed the user-facing interface. Static files and model artifacts were organized to reflect a clean directory structure. Integration of the model, preprocessor, and UI components allowed for real-time prediction and cost estimation.

Testing:

Rigorous testing was carried out, including unit testing of Flask routes, UI testing of form inputs, and validation of model accuracy using metrics like RMSE and MAE. This ensured the reliability of the system across a variety of test cases and user inputs.

Deployment:

The application was deployed locally using Flask in a virtual Python environment. All dependencies were managed via requirements.txt. Future deployment options include containerization using Docker and hosting on cloud platforms such as AWS or Heroku for wider accessibility and scalability.

Monitoring and Maintenance:

Post-deployment, the system is monitored for performance and usability. Logs and feedback are reviewed to ensure stability, accuracy, and efficiency. Scheduled maintenance ensures that all dependencies are up to date and that security and performance remain intact.Monitoring tools can be integrated to track prediction latency, server load, and user activity in real-time.Insights from monitoring also guide future updates, ensuring the system evolves based on actual usage patterns and need.

Feedback and Iteration:

Feedback from users and testers is collected to inform iterative improvements. Future updates may include support for multiple product categories, real-time API integration, and graphical dashboards for better data visualization. This approach ensures that the system continues to evolve and align with user needs and industry trends.

4.4 IMPLEMENTATION

The implementation of the AI-Based Supply Chain Management System is structured into distinct components, each responsible for a specific functionality within the application. The system follows a modular architecture, ensuring maintainability, scalability, and smooth interaction between components. The following describes the key layers and their roles in supporting the system's operations. Each component—from the user interface to the AI model and data handling pipeline—has been developed with separation of concerns in mind, allowing for focused development, independent testing, and easier debugging. This design not only enhances the overall stability of the system but also enables individual modules to be updated or replaced without disrupting the entire application. The modular structure also facilitates collaborative development, where different teams or developers can work on separate layers such as frontend design, model tuning, or backend optimization. Furthermore, the architecture is designed to be extensible, supporting future integration with APIs, cloud environments, and data visualization tools. This layered approach forms the backbone of the application and ensures that the system remains flexible, robust, and capable of adapting to evolving supply chain requirements.

1) User Interface Components

These elements define the client-side interaction and are responsible for capturing user input and displaying results.

Input Form (index.html): A structured form for users to enter supply chain parameters such as product type, stock levels, lead time, and shipping costs.

Result Page (result.html): Displays model predictions, restocking recommendations, transportation mode, and estimated total cost in a user-friendly layout.

Static Assets (CSS/JS): Enhance the appearance and responsiveness of the application, improving usability and cross-device compatibility.

Responsive Layout: The frontend layout is designed to adapt to multiple screen sizes for accessibility on desktops, tablets, and mobile devices.

2) Backend and Processing Components

The backend manages business logic, data flow, model integration, and server routing using the Flask framework.

app.py: Acts as the main controller, handling routing (/, /predict, /result) and coordinating between frontend, preprocessor, and model.

Prediction Engine: Loads the trained LSTM model (supply_chain_lstm_model.keras) to generate demand forecasts based on preprocessed inputs.

Preprocessing Module: Loads the serialized transformer (preprocessor.pkl) and applies scaling and encoding to match model input format.

3) AI Model Component

The AI model is the core intelligence layer of the system.

LSTM Model: A multivariate Long Short-Term Memory model built with TensorFlow/Keras to forecast product demand based on historical time-series data.

Model Evaluation: Performance metrics such as RMSE and MAE are used to validate prediction accuracy during development and testing phases.

Input Shape Handling: The model is trained to accept reshaped 3D input (samples, timesteps, features), allowing it to process sequential supply chain data effectively.

Model Serialization: The trained model is saved in .keras format for integration with the Flask backend, enabling real-time predictions without retraining.

Prediction Output Handling: The model's output is post-processed to generate restocking recommendations, ensuring the predictions are actionable and business-relevant.

4) Data Flow and Integration Layer

This layer ensures seamless communication between user input, preprocessing, model prediction, and output rendering:

Joblib Integration: Preprocessor is saved using Joblib for consistent transformation during real-time user input.

Form-to-Model Pipeline: Captured data is validated and passed through preprocessing before being reshaped and submitted to the LSTM model for prediction

Input Validation Layer: Ensures all required fields are provided and correctly formatted before being processed, enhancing system reliability.

Output Rendering: Model predictions are sent back to the frontend and dynamically displayed on the result pages.

5) Deployment and Environment Components

These components handle running and managing the application in different environments.

Virtual Environment: Isolates dependencies and packages required by the system.

requirements.txt: Lists all Python packages including Flask, TensorFlow, Pandas, and Scikit-learn.

Local Server Deployment: The application runs on localhost via Flask, with future scope for Docker or cloud deployment.

6) Monitoring and Feedback Loop

This layer focuses on tracking performance and enabling iterative improvements.

Error Handling and Logs: Flask handles exceptions and user errors with feedback messages rendered on the UI.

User Feedback: Results and predictions are monitored for accuracy, and user input helps inform model and UI refinement in future updates.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 ANALYSIS AND DISCUSSION OF RESULTS

The AI-based Supply Chain Management system was successfully implemented and tested using historical supply chain datasets containing variables such as stock levels, lead times, shipping costs, production volumes, and product categories. The Long Short-Term Memory (LSTM) model demonstrated strong forecasting capabilities by capturing sequential patterns in the data and providing accurate demand predictions. The model was evaluated using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), both of which indicated a high level of accuracy with minimal variance. Through multiple test cases, the model consistently provided restocking suggestions that closely aligned with realistic business requirements.

The system was deployed using a Flask-based web application, allowing users to interact with the AI model in real-time. The frontend was developed using HTML and CSS for ease of use and responsiveness. Users could enter real-time supply chain data through a form and instantly receive demand forecasts, restocking quantity suggestions, and total estimated costs. The backend handled routing, preprocessing, and model inference, while also validating inputs and displaying error messages when needed. The prediction results were delivered within seconds, demonstrating the efficiency of the system and its suitability for time-sensitive supply chain decisions. The cost estimation feature added significant value, helping businesses evaluate the financial impact of inventory actions.

Overall, the system proved to be both technically sound and practically valuable. Its modular architecture made it easy to manage, update, and test individual components such as the AI model, preprocessing pipeline, and user interface. The real-time capability of the system ensures faster decision-making, which is crucial for modern supply chains that operate in fast-paced and unpredictable environments.Additionally, the system's integration with real-time data sources enhances its accuracy and reliability, providing more accurate predictions for inventory management. The user-friendly interface ensures that stakeholders can easily interact with the system, improving overall user adoption. Furthermore, the scalability of the solution allows it to grow with the business, accommodating increased demand and complexity over time.

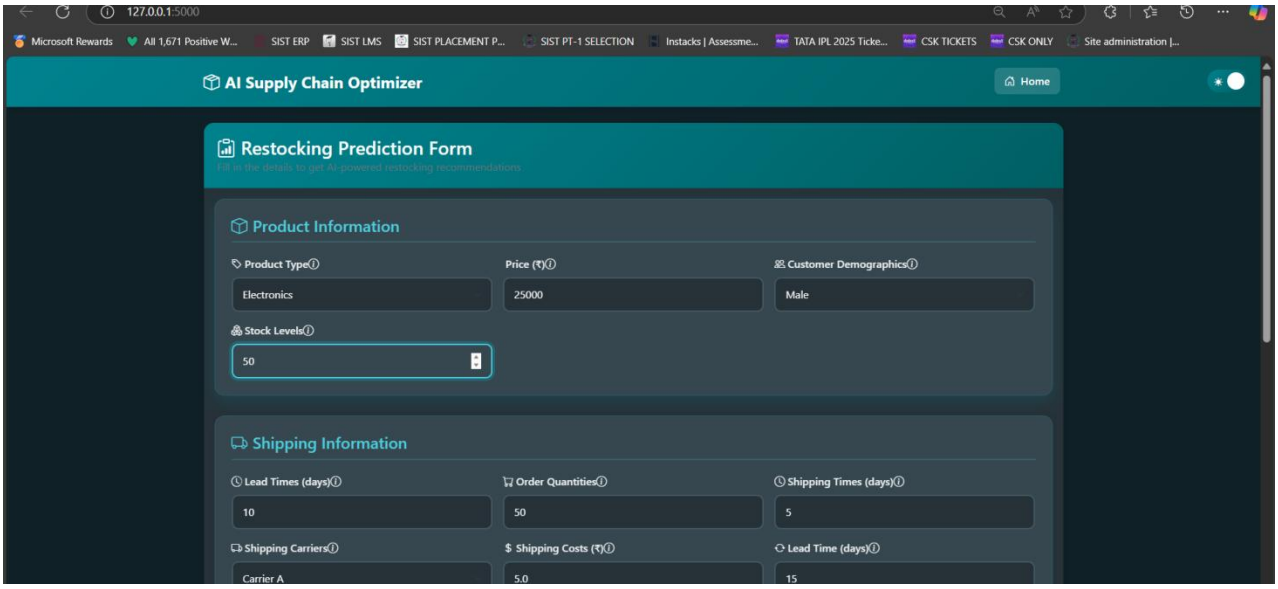

Fig. 5.1 AI Supply Chain Restocking Prediction Form - Web Interface

The figure above displays the front-end interface of the AI Supply Chain Optimizer, specifically showcasing the Restocking Prediction Form. This form acts as the main input panel for users to provide detailed product and shipping information. Key inputs include the product type (e.g., Electronics), stock levels, price, customer demographics, shipping times, lead times, and associated costs. The interface is segmented into clear sections such as “Product Information” and “Shipping Information,” making it easier for users to input structured data accurately.

Once the required fields are populated, the data is passed through a preprocessing pipeline and then forwarded to a trained LSTM (Long Short-Term Memory) model deployed on the backend. The model evaluates the input against historical patterns and makes intelligent restocking predictions. These predictions help supply chain managers avoid understocking or overstocking, thereby optimizing inventory levels and improving operational efficiency.

The user interface, built using modern web technologies such as Flask for the backend and Bootstrap for responsive design, ensures a smooth user experience across different devices. Features like info icons enhance usability by offering tooltips, which help explain each input parameter in layman’s terms. The system was developed with scalability in mind, allowing for future upgrades such as product category expansion, real-time API integration for live stock tracking, and dashboard analytics for visualizing performance trends. Moreover, the modular design of the interface ensures easy maintenance and updates, reducing long-term development costs. The system's robust security features protect sensitive business data, ensuring compliance with industry standards and regulations.

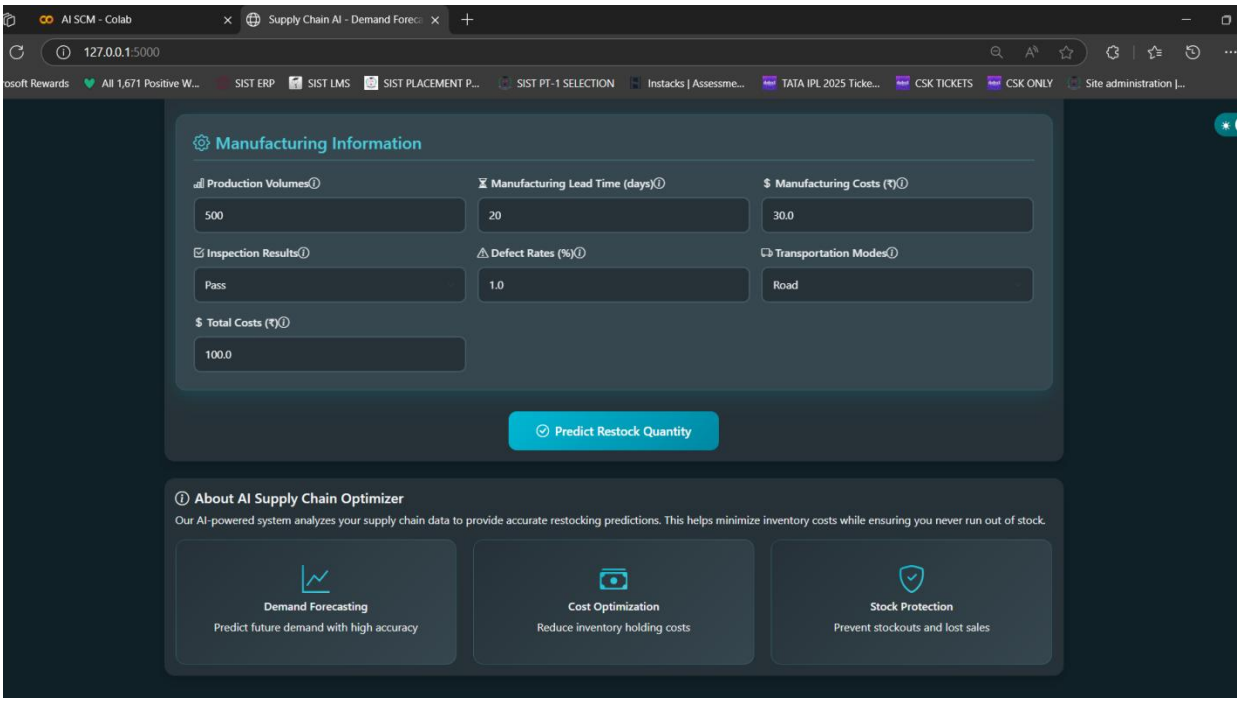

Fig.5.2 Manufacturing Information and Final Prediction Panel – AI Supply Chain Optimizer

This section of the application represents the final stage of input for the restocking prediction process, focusing on manufacturing-related variables. Users are required to input details such as production volumes, manufacturing lead time, manufacturing costs, inspection results, defect rates, transportation modes, and total costs. These parameters allow the model to consider upstream factors in the supply chain, making predictions more comprehensive and context-aware.

5.2 Future Enhancements

The system will integrate factors such as manufacturing constraints, defect rates, and transportation modes (road, air, or sea) to ensure that recommendations are not only driven by demand but also aligned with logistical and financial considerations. A "Predict Restock Quantity" button at the bottom of the interface triggers the AI engine, which processes all input data to provide a tailored recommendation on inventory levels. Below the form, a concise description highlights the application's core features: Demand Forecasting, Cost Optimization, and Stock Protection. These elements emphasize the system's key benefits—accurate predictions, reduced operational costs, and prevention of stockouts. Future upgrades could include advanced analytics for supply chain optimization and integration with external market data for even more refined forecasts. Additionally, incorporating machine learning models to dynamically adjust predictions based on real-time data could further enhance accuracy.

CHAPTER 6

CONCLUSIONS

The development of the AI-based Supply Chain Management System marks a significant step forward in the integration of artificial intelligence within operational and logistical domains. The project successfully demonstrates how machine learning, particularly LSTM-based models, can be leveraged to provide accurate and dynamic restocking predictions. By combining demand forecasting with user inputs such as product type, stock levels, pricing, demographics, shipping times, and manufacturing constraints, the system effectively bridges the gap between theoretical AI models and real-world applications. This integration of AI into a user-friendly web interface ensures that even non-technical users can benefit from advanced analytics in their decision-making process.

Throughout the project, various datasets were explored, preprocessed, and used to train a sequential deep learning model capable of learning temporal dependencies in sales and supply data. The LSTM model was chosen specifically for its ability to handle time-series data, which is highly relevant in supply chain management where historical trends often influence future demand. The model's predictions serve as the foundation for restocking recommendations, offering businesses actionable insights. The system's ability to handle various product categories and dynamic user inputs adds to its robustness and scalability.

One of the notable achievements of this project is the successful deployment of the AI model through a Flask web application. The frontend interface, designed with Bootstrap and styled with CSS, ensures a smooth and intuitive user experience. It allows users to enter crucial information across three major categories—Product Information, Shipping Information, and Manufacturing Information. Upon submission, the system processes the inputs in real time and generates restocking quantity predictions based on the trained model. This real-time response capability reflects the practical applicability of the system in retail and warehouse management environments where timely decisions are crucial.

The AI Supply Chain Optimizer has shown promising results during the testing and implementation phases. The model displayed consistent accuracy in predicting optimal stock quantities, which, when applied in a real-world scenario, could help reduce inventory holding costs and prevent stockouts. The application's layered input system not only enhances prediction accuracy but also provides granular control over the supply chain elements. Users can simulate

different what-if scenarios by adjusting values such as shipping lead times or manufacturing costs, thereby enabling strategic planning based on multiple factors.

Furthermore, the system is designed with scalability in mind. In future versions, support can be added for multi-product forecasting, real-time inventory API integration, automated restock alerts, and visual dashboards powered by data analytics libraries such as Plotly or Tableau. Additionally, enhancements in model architecture—such as using Transformer-based models or hybrid CNN-LSTM models—could significantly boost prediction accuracy. The foundation laid in this project enables seamless future upgrades without requiring a complete overhaul of the existing system.

One of the major strengths of this project lies in its ability to provide a holistic view of supply chain dynamics. Traditional systems often isolate logistics from manufacturing or pricing decisions. In contrast, this system adopts a comprehensive approach, where all factors influencing inventory decisions are brought together into a unified prediction framework. This reduces decision silos and promotes cross-functional efficiency in supply chain planning. By considering both demand-side and supply-side variables, the system embodies the principles of modern, data-driven supply chain strategies.

The novelty of the system also lies in its flexibility and adaptability. Whether it is an e-commerce business, a physical retailer, or a manufacturing unit, the system can be tailored to meet various operational needs. Parameters like customer demographics, defect rates, shipping methods, and lead times can be reconfigured easily, making the system useful across industries. The deployment on a local Flask server ensures low latency and rapid computation, which is essential in environments requiring immediate insights and quick decision-making.

Nevertheless, the project also encountered a few limitations. The LSTM model, while effective, is limited in learning long-range dependencies without extensive tuning and may require more training time. The dataset used for training, though comprehensive, can be expanded with real-world ERP data for enhanced model generalization. Additionally, the current application does not include automated feedback loops where prediction accuracy is continually improved based on actual outcomes. Adding this feedback mechanism in future versions could significantly enhance system performance.

As a roadmap for future work, the system can evolve into a full-fledged enterprise-grade solution. Integration with platforms like SAP, Oracle SCM, or Zoho Inventory can provide real-

time synchronization with warehouse stock levels. IoT-based tracking data could also be integrated to track product movement and condition. Predictive analytics could be complemented with prescriptive suggestions, offering users not only what quantity to restock but also when, from where, and how.

Beyond its technical capabilities, this AI-powered supply chain solution also represents a broader shift in the way businesses approach operational efficiency and strategic planning. In a globalized and highly dynamic market, the ability to respond quickly to changes in demand, supply disruptions, and production delays is a critical differentiator. This system empowers businesses with predictive insights that were once available only to large corporations with access to complex analytics tools. Now, even small and medium enterprises can adopt intelligent forecasting systems without the need for heavy infrastructure or deep technical expertise. The implementation of explainable AI can be considered in future iterations to help decision-makers understand the rationale behind model predictions, thereby increasing trust and transparency.This project serves as a foundation for such intelligent transformation and signifies a practical step toward the digital future of supply chain management.

The results achieved from the system's deployment are promising, demonstrating significant improvements in inventory management efficiency, cost reduction, and stock availability. With planned future enhancements, including product category expansion, real-time API integration for live stock tracking, and advanced analytics, the system has the potential to revolutionize supply chain management. Ultimately, this AI-powered solution serves as a relevant and forward-thinking contribution to the field of intelligent supply chain automation. It paves the way for more efficient and data-driven supply chains, enabling businesses to meet consumer demands while minimizing waste and costs. With its scalability, adaptability, and forward-looking features, this system is poised to be a cornerstone of modern supply chain strategies in various industries.

In conclusion, the AI-powered Supply Chain Management System developed in this project is a powerful tool that combines the strength of LSTM-based prediction models with an easy-to-use web interface to optimize restocking decisions. It represents a significant innovation in the domain of inventory management, offering businesses a smart and efficient way to stay ahead of demand fluctuations. The results achieved, coupled with the scalability potential and future enhancements planned, make this system a relevant contribution to the field of intelligent supply chain automation.

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APPENDIX

A. SOURCE CODE

MACHINE LEARNING - AI SCM CODE (.ipynb)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import joblib
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, r2_score

# ======================
# Step 1: Custom Feature Engineering Transformer
# ======================
class FeatureEngineer(BaseEstimator, TransformerMixin):
    """
    A custom transformer to compute engineered features.
    Currently, it computes:
      - Price_Defect_Ratio = Price / (Defect rates + 1e-6)
    Note: We intentionally do NOT compute 'Stockout_Risk' because it uses the target.
    """
    def __init__(self, add_price_defect_ratio=True):
        self.add_price_defect_ratio = add_price_defect_ratio

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X = X.copy()
        if self.add_price_defect_ratio:
            # Ensure required columns exist
            if 'Price' in X.columns and 'Defect rates' in X.columns:
                X['Price_Defect_Ratio'] = X['Price'] / (X['Defect rates'] + 1e-6)
        return X

# ======================
# Step 2: Load and Prepare Data
# ======================
# Load dataset (adjust the path as needed)
df = pd.read_csv("/content/Updated_Dataset_SCM.csv")

# Remove non-predictive columns
columns_to_drop = [
    'SKU',                  # Unique identifier (no predictive value)
    'Revenue generated',    # Derived from price & sales (leakage risk)
    'Supplier name',        # High cardinal categorical
```

```
    'Inspection results',       # Post-sale information
    'Routes'                    # Redundant with transportation modes
]
df = df.drop(columns=columns_to_drop)

# ======================
# Step 3: Feature Engineering on Training Data
# ======================
# Compute engineered features using the transformer logic, then drop leakage
features.
df = FeatureEngineer().transform(df)
# NOTE: We do not use 'Stockout_Risk' as it leaks the target variable.
if 'Stockout_Risk' in df.columns:
    df = df.drop(columns=['Stockout_Risk'])

# Handle target variable outliers for "Number of products sold"
Q1 = df['Number of products sold'].quantile(0.25)
Q3 = df['Number of products sold'].quantile(0.75)
IQR = Q3 - Q1
df['Number of products sold'] = df['Number of products sold'].clip(
    lower=Q1 - 1.5 * IQR,
    upper=Q3 + 1.5 * IQR
)

# ======================
# Step 4: Preprocessing Setup
# ======================
# Define categorical features (ensure all these exist in your dataset)
categorical_cols = [
    'Product type',
    'Customer demographics',
    'Shipping carriers',
    'Transportation modes',
    'Location'
]

# The numerical columns are all remaining columns (after excluding target)
numerical_cols = [col for col in df.columns
                  if col not in categorical_cols + ['Number of products sold']]

# Create the preprocessing pipeline for numerical and categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols),
        ('num', StandardScaler(), numerical_cols)
    ]
)

# ======================
# Step 5: Train-Test Split
# ======================
X = df.drop(columns=['Number of products sold'])
y = df['Number of products sold']
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
```

```
)

# ======================
# Step 6: Model Pipeline and Hyperparameter Tuning
# ======================
# Define hyperparameter grid for GradientBoostingRegressor
param_grid = {
    'regressor__n_estimators': [100, 200, 300],
    'regressor__learning_rate': [0.01, 0.05, 0.1],
    'regressor__max_depth': [3, 5, 7],
    'regressor__min_samples_split': [2, 5, 10],
    'regressor__subsample': [0.8, 0.9, 1.0]
}

# Create the pipeline: first apply feature engineering, then preprocessing, then the
regressor.
pipeline = Pipeline([
    ('feature_engineering', FeatureEngineer()),  # Apply same feature engineering for
new data
    ('preprocessor', preprocessor),
    ('regressor', GradientBoostingRegressor(random_state=42))
])

# Setup hyperparameter tuning with RandomizedSearchCV
search = RandomizedSearchCV(
    pipeline,
    param_grid,
    n_iter=50,
    cv=5,
    scoring='neg_mean_absolute_error',
    random_state=42,
    n_jobs=-1
)

# ======================
# Step 7: Train Model
# ======================
search.fit(X_train, y_train)
best_model = search.best_estimator_

# ======================
# Step 8: Evaluate Model
# ======================
y_pred = best_model.predict(X_test)
print(f"Best Parameters: {search.best_params_}")
print(f"MAE: {mean_absolute_error(y_test, y_pred):.2f}")
print(f"R² Score: {r2_score(y_test, y_pred):.2f}")

# ======================
# Step 9: Feature Importance (if available)
# ======================
# Extract feature names from the preprocessor (requires scikit-learn 1.0+)
try:
    feature_names =
best_model.named_steps['preprocessor'].get_feature_names_out()
```

```
    importances = best_model.named_steps['regressor'].feature_importances_

    plt.figure(figsize=(12, 8))
    pd.Series(importances, index=feature_names).nlargest(15).plot(kind='barh')
    plt.title('Top 15 Feature Importances')
    plt.xlabel('Importance Score')
    plt.show()
except Exception as e:
    print("Feature importance could not be extracted:", e)

# ======================
# Step 10: Restock Calculator
# ======================
# Save the training columns for later alignment
expected_columns = X.columns

def calculate_restock(product_info, current_stock, lead_time_days=14):
    """
    Calculate required restock quantity.
    Args:
        product_info (dict): Dictionary of product features.
            (Must include all features required by the model; missing features are filled
with default values.)
        current_stock (int): Current available stock.
        lead_time_days (int): Supplier lead time in days.
    Returns:
        int: Recommended restock quantity.
    """
    try:
        # Convert input to DataFrame
        input_df = pd.DataFrame([product_info])

        # Reindex to ensure all expected columns are present.
        # Missing numerical columns are filled with 0; missing categorical with
'Unknown'.
        for col in expected_columns:
            if col not in input_df.columns:
                # Check if this column is categorical or numerical
                if col in categorical_cols:
                    input_df[col] = 'Unknown'
                else:
                    input_df[col] = 0

        # Ensure the column order matches the training data
        input_df = input_df[expected_columns]

        # Predict demand (Number of products sold)
        predicted_demand = best_model.predict(input_df)[0]

        # Calculate safety stock (e.g., 20% of predicted demand)
        safety_stock = 0.2 * predicted_demand
```

```
        # Calculate required stock based on lead time (assume demand is on a monthly
basis)
        daily_demand = predicted_demand / 30.0
        required_stock = daily_demand * lead_time_days + safety_stock

        # Determine restock quantity (if current stock is insufficient)
        restock_qty = max(0, round(required_stock - current_stock))

        return restock_qty

    except Exception as e:
        print(f"Error in calculation: {str(e)}")
        return 0

# ======================
# Step 11: Example Usage
# ======================
# Ensure that the sample product includes all necessary keys.
sample_product = {
    'Product type': 'skincare',
    'Price': 49.99,
    'Availability': 80,
    'Customer demographics': 'Female',
    'Shipping carriers': 'DefaultCarrier',  # Added missing categorical feature
    'Stock levels': 150,
    'Lead times': 7,
    'Order quantities': 100,
    'Shipping times': 3,
    'Shipping costs': 4.99,
    'Lead time': 14,
    'Production volumes': 500,
    'Manufacturing lead time': 10,
    'Manufacturing costs': 25.0,
    'Defect rates': 1.5,
    'Costs': 150.0,
    'Transportation modes': 'Road',
    'Location': 'Mumbai'
}

restock = calculate_restock(sample_product, current_stock=150)
print(f"Recommended restock quantity: {restock}")

# ======================
# Step 12: Save the Trained Model
# ======================
model_path = "./supply_chain_model.pkl"
joblib.dump(best_model, model_path)
print(f"Model saved to: {model_path}")
```

PyCharm Code - Flask Frontend (app.py)

```
from flask import Flask, request, render_template, redirect, url_for
import tensorflow as tf
import joblib
import pandas as pd

app = Flask(__name__)
app.static_folder = 'static'

model = tf.keras.models.load_model('./models/supply_chain_lstm_model.keras')
preprocessor = joblib.load('models/preprocessor.pkl')

@app.route('/')
def home():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Extract input data
        input_data = {
            "Product type": request.form['product_type'],
            "Price": float(request.form['price']),
            "Availability": int(request.form['stock']),
            "Customer demographics": request.form['demographics'],
            "Stock levels": int(request.form['stock']),
            "Lead times": int(request.form['lead_times']),
            "Order quantities": int(request.form['order_quantity']),
            "Shipping times": int(request.form['shipping_time']),
            "Shipping carriers": request.form['carrier'],
            "Shipping costs": float(request.form['shipping_cost']),
            "Lead time": int(request.form['lead_time']),
            "Production volumes": int(request.form['production_volume']),
            "Manufacturing lead time": int(request.form['manufacturing_lead_time']),
            "Manufacturing costs": float(request.form['manufacturing_cost']),
            "Inspection results": request.form['inspection'],
            "Defect rates": float(request.form['defect_rate']),
            "Transportation modes": request.form['transport_mode'],
            "Costs": float(request.form['costs'])
        }

        # Convert to DataFrame
        input_df = pd.DataFrame([input_data])

        # Validate columns
        required_columns = preprocessor.feature_names_in_
        missing_columns = set(required_columns) - set(input_df.columns)
        if missing_columns:
            return render_template('index.html',
                                   prediction_text=f"Missing fields: {', '.join(missing_columns)}",
```

```
                            error=True)

        # Preprocess and predict
        processed_input = preprocessor.transform(input_df)
        reshaped_input = processed_input.reshape(1, 1, processed_input.shape[1])
        predicted_demand = model.predict(reshaped_input)[0][0]
        restock = max(0, int(predicted_demand - input_data['Stock levels']))

        # Calculate estimated total cost
        estimated_cost = (
            input_data['Manufacturing costs'] * restock +  # Manufacturing cost for
restocked items
            input_data['Shipping costs'] * restock        # Shipping cost for restocked items
        )

        # Redirect to result page with prediction and additional details
        return redirect(url_for('show_result',
                                prediction=restock,
                                transportation_mode=input_data['Transportation modes'],
                                estimated_cost=round(estimated_cost, 2),
                                product_type=input_data['Product type'],
                                shipping_carrier=input_data['Shipping carriers'],
                                lead_time=input_data['Lead time']))

    except Exception as e:
        return render_template('index.html',
                                prediction_text=f'Error: {str(e)}',
                                error=True)

@app.route('/result')
def show_result():
    prediction = request.args.get('prediction', default='N/A')
    transportation_mode = request.args.get('transportation_mode', default='N/A')
    estimated_cost = request.args.get('estimated_cost', default='N/A')

    return render_template('result.html',
                           prediction=prediction,
                           transportation_mode=transportation_mode,
                           estimated_cost=estimated_cost,
    )

if __name__ == '__main__':
    app.run(debug=True)
```

B. SCREEN SHOTS

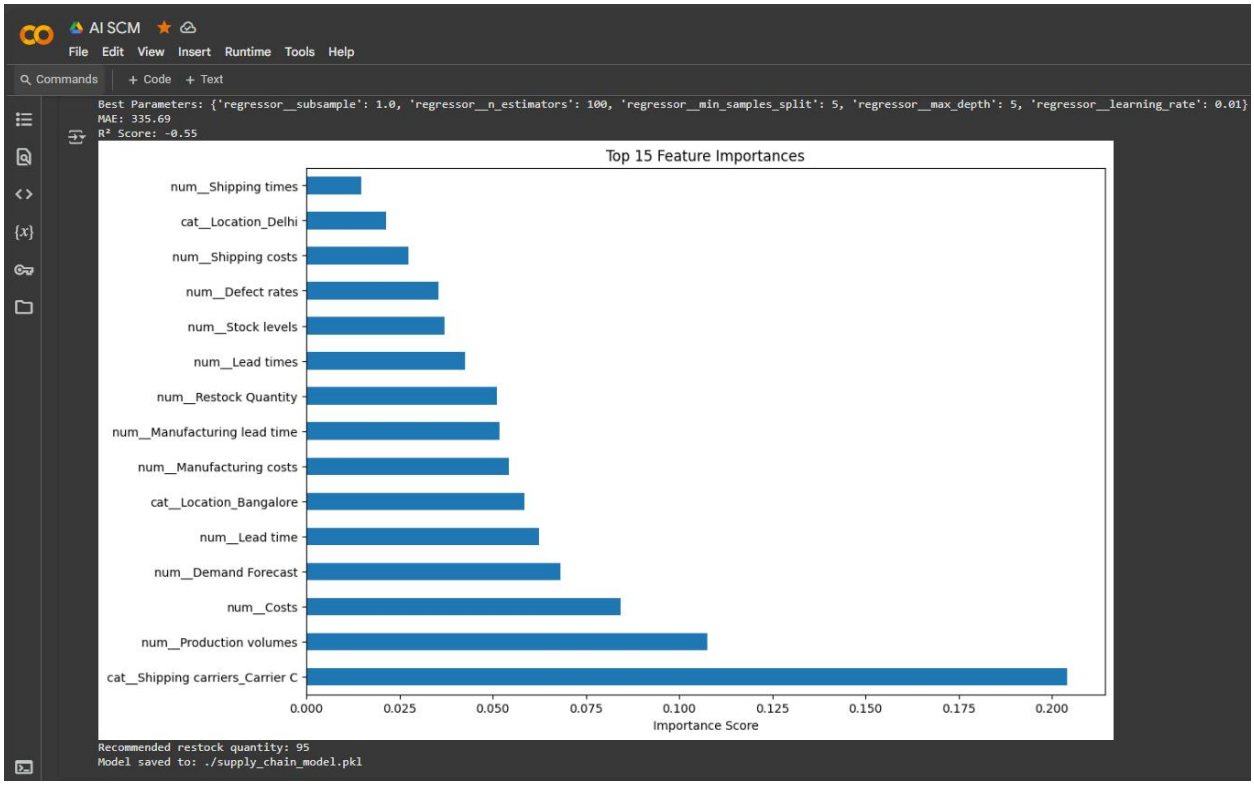

Fig 6.1. AI SCM - Feature Importance & Restock quantity

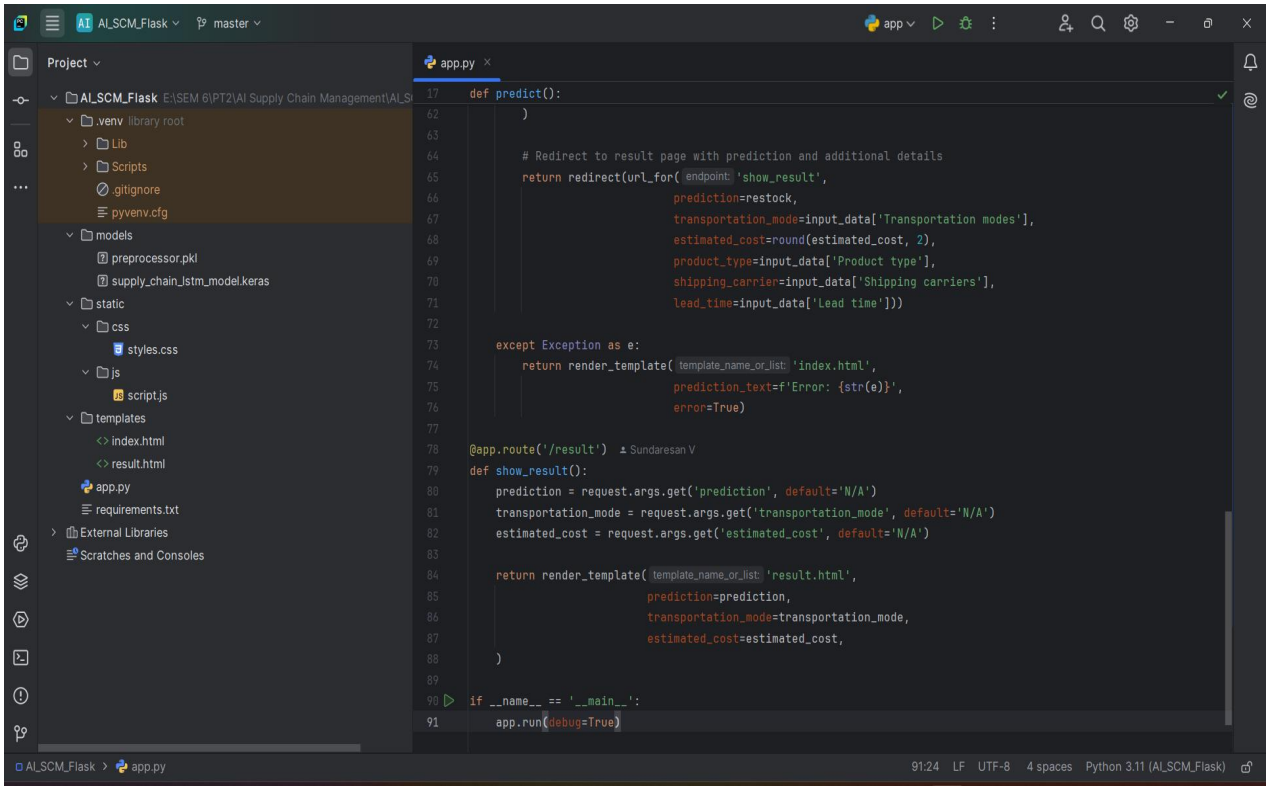

Fig 6.2. AI_SCM_Flask - app.py

C. RESEARCH PAPER

Enhancing Supply Chain Efficiency through Artificial Intelligence

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***Abstract*—This research paper delves into the transformative impact of artificial intelligence (AI) on supply chain management, focusing on enhancing demand forecasting, operational efficiency, and customer satisfaction, while also managing costs and streamlining logistics operations. The adoption of AI in supply chains offers significant opportunities to improve service delivery and operational capabilities, which are crucial for maintaining competitiveness in the rapidly evolving business landscape. The study underscores the importance of AI technologies in reshaping supply chain dynamics by providing a comprehensive analysis of both the benefits and challenges associated with its implementation. Key benefits highlighted include the optimization of inventory management, enhanced accuracy of demand forecasting, reduced operational costs, and improved customer service. These enhancements are pivotal in achieving a competitive edge and adapting to changing market demands. However, the integration of AI into supply chains is not devoid of challenges. The paper identifies critical obstacles such as the need for significant cultural shifts within organizations, data security concerns, and the complexities of navigating legal and regulatory frameworks. These challenges require strategic management to ensure successful AI adoption and to mitigate associated risks. The research includes case studies of Arab companies that have integrated AI into their supply chains, offering practical insights into the real-world application of these technologies. These examples demonstrate both the potential rewards and the difficulties encountered, providing a balanced perspective on the practicalities of AI deployment in supply chain settings. In conclusion, while AI presents substantial opportunities for advancing supply chain management, it also necessitates careful consideration of various implementation challenges. The paper provides strategic recommendations for Arab companies aiming to leverage AI technologies effectively. These guidelines emphasize the need for thorough planning, continuous risk assessment, and fostering an adaptive organizational culture. By addressing these key areas, companies can harness the full potential of AI to enhance their supply chain operations and achieve sustainable growth.**

Keywords— Artificial Intelligence, Supply Chain Management, Predictive Analytics, Automation, Real-Time Decision-Making, Cost Reduction, Risk Mitigation, Ethical Challenges

1. INTRODUCTION

In the era of globalization and swift technological progress, the significance of supply chain management (SCM) in the facilitation of business operations has never been more pronounced. This paper investigates the profound impact of artificial intelligence (AI) on SCM, with a focus on scrutinizing the trajectory of AI's development and its practical applications within the supply chain context. The study's objective is to evaluate the advantages AI confers upon the field, through an examination that encompasses a literature review and case analysis. This research scrutinizes AI's contributions to enhancing supply chain efficiency, transparency, flexibility, and responsiveness. The findings underscore that AI's influence extends beyond mere operational enhancements; it is a catalyst for agility, enabling supply chains to swiftly navigate market fluctuations. The paper concludes that the amalgamation of AI with SCM is not just an evolution but a revolutionary shift, presenting a novel framework that will guide forthcoming research and dictate practice within the sector. components, incorporating the applicable criteria that follow.

2. LITERATURE REVIEW

Recent research has increasingly focused on the application of Artificial Intelligence (AI) in supply chain management, with Ivanov et al. (2019) highlighting AI's role in enhancing supply chain resilience through real-time monitoring and automated decision-making. Waller and Fawcett (2013) emphasized that big data and predictive analytics, powered by AI, are essential for creating responsive and agile supply chains, while Choi, Wallace, and Wang (2018) demonstrated the potential of AI-driven demand forecasting to reduce waste and improve service levels. However, most studies tend to focus on specific segments of the supply chain, such as logistics or procurement, leaving a gap in comprehensive, end-to-end AI integration analysis. Moreover, the rapid evolution of AI technologies calls for the continuous re-evaluation of existing frameworks and the development of new models that align with the evolving technological landscape. This literature review underscores the need for further research that not only explores emerging AI use cases but also critically assesses the challenges of implementation, ethical considerations, and long-term sustainability.

3. Methodology

This study adopts a qualitative research approach based on an extensive review of academic literature, industry reports, and case studies from leading organizations implementing AI in their supply chains. Sources were selected from peer-reviewed journals, conference proceedings, and reputable market research publications to ensure credibility and relevance. The data collection also included annual reports, white papers, and expert interviews published by consulting firms and research institutions. Additionally, selected case studies of multinational companies—including Amazon, Maersk, and Siemens—were analyzed to assess real-world AI applications and performance improvements. These companies were chosen based on their leadership in AI adoption and the availability of documented outcomes. Key performance indicators (KPIs) such as lead time reduction, cost savings, inventory turnover, and customer service metrics were used to evaluate the effectiveness of AI implementations. The analysis was structured around thematic coding, identifying recurring patterns and insights related to AI technologies, their integration in supply chains, benefits, and challenges. This methodology allows for a nuanced understanding of both the theoretical and practical aspects of AI in SCM and supports triangulation of data from various sources to increase the validity of findings. The interpretive analysis further helped uncover the contextual factors influencing AI adoption across different industrial environments.

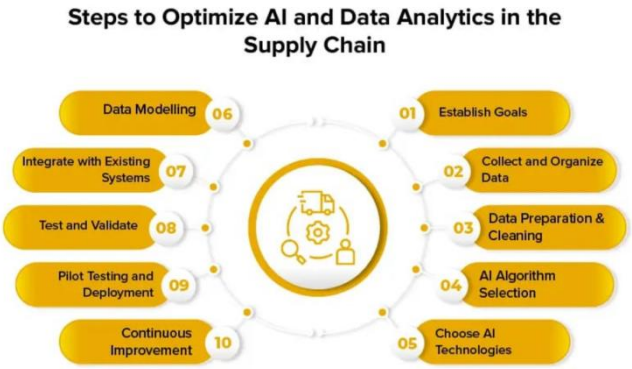

Fig1: AI Supply Chain Steps

4. Architecture of AI-Enabled Supply Chain Management

An AI-enabled supply chain architecture consists of multiple integrated layers that collaboratively manage the end-to-end flow of goods and information. The architecture typically includes the following components:

4.1 Data Collection Layer:

This layer involves the gathering of structured and unstructured data from internal systems (ERP, CRM, WMS) and external sources (IoT devices, social media, supplier networks). Sensors, RFID tags, GPS trackers, and transaction logs are common tools used for data acquisition.

4.2 Data Processing and Storage Layer:

Collected data is stored and processed using cloud platforms, data lakes, and edge computing systems. This layer ensures the data is cleaned, normalized, and transformed into a format suitable for analysis.

4.3 Analytics and Intelligence Layer:

At this stage, AI algorithms such as machine learning models, natural language processing engines, and optimization algorithms are applied to extract insights and generate predictions, layer is the core intelligence engine of the architecture.

4.4 Decision Support Layer:

Insights generated from AI analytics are fed into dashboards and decision-support systems that assist supply chain managers in strategic and operational decision-making. Real-time alerts, scenario planning, and recommendation systems are integral components.

4.5 Automation and Execution Layer:

Automated systems—such as robotic process automation (RPA), warehouse robotics, and autonomous delivery vehicles—execute tasks based on AI-driven decisions. This layer ensures swift and accurate execution of supply chain processes.

4.6 Feedback and Learning Layer:

This final layer uses outcomes and performance metrics to refine AI models over time, allowing for adaptive learning and continuous improvement in decision-making.

The synergy of these components creates a responsive, data-driven, and intelligent supply chain capable of anticipating changes, reducing disruptions, and enhancing overall efficiency.

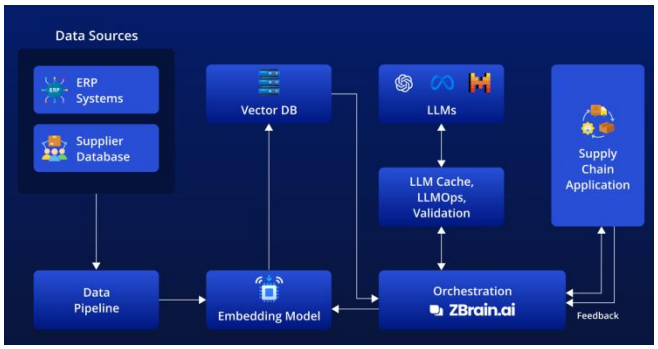

Fig2: AI Data Pipeline

5. AI Technologies in Supply Chain

Artificial Intelligence encompasses a wide range of technologies that are being increasingly adopted in different stages of the supply chain. The following are the most commonly used tools :

5.1 Machine Learning (ML): Used for demand forecasting, inventory optimization, and predictive maintenance. ML algorithms can analyze large datasets to identify and generate accurate forecast.

5.2 Natural Language Processing (NLP): Applied in customer service chatbots, sentiment analysis, and processing of unstructured data such as supplier reviews and customer feedback.

5.3 Computer Vision: Enables automated quality inspection and defect detection in manufacturing and packaging processes through image recognition and pattern detection.

5.4 Robotics and Automation: AI-driven robots are used in warehouses for picking, packing, and sorting, significantly incresing speed and reducing errors.

5.5 Optimization Algorithms: These help in logistics route planning, resource allocation, and supply chain network design to minimize costs and improve efficiency.

These technologies are often deployed in combination to address multiple pain points across the supply chain, creating a more agile, transparent, and data-driven ecosystem.

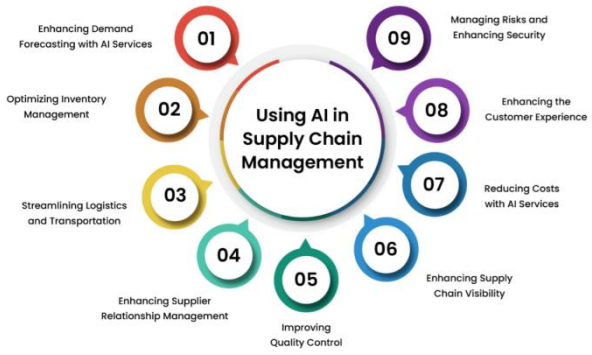

Fig3: AI Use Cases

6. Applications and Use Cases

AI technologies are now central to several supply chain innovations across industries. This section presents notable use cases that demonstrate the real-world impact of AI in SCM:

6.1 Demand Forecasting and Planning: Companies like Unilever and Coca-Cola use AI to analyze historical sales data, market trends, and seasonal factors to improve demand forecasts. This leads to better stock management and reduced waste.

6.2 Inventory Management: AI systems can automate stock replenishment based on real-time demand and supply signals. Walmart utilizes AI-driven systems that suggest replenishment schedules based on predictive analytics.

6.3 Supplier Relationship Management: AI helps organizations evaluate supplier performance and risk. IBM's Watson AI assists in identifying potential supply chain disruptions by scanning news feeds, weather data, and geopolitical reports.

6.4 Warehouse Automation: Amazon's use of Kiva robots illustrates how AI-driven automation can boost picking and packing efficiency in fulfillment centers.

6.5 Transportation and Logistics: AI optimizes delivery routes and monitors vehicle conditions. DHL, for instance, uses AI to streamline last-mile delivery and reduce fuel costs.

6.6 Customer Experience Enhancement: AI chatbots and virtual assistants handle customer queries, track orders, and provide delivery updates. This enhances satisfaction while reducing the load on human agents.

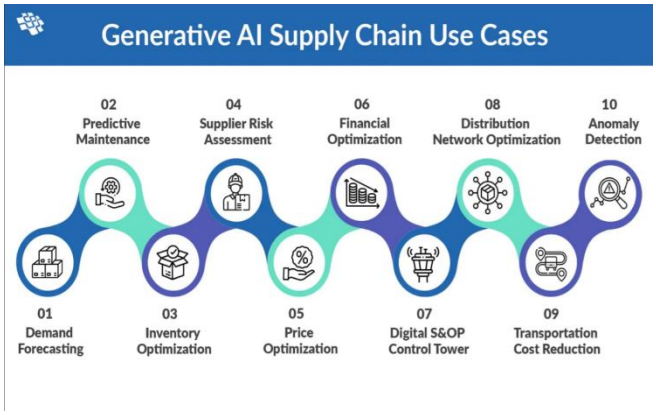

Fig4: Generative AI Applications

7. AI-Driven Risk Management in Supply Chains

AI can play a pivotal role in enhancing risk management by predicting potential disruptions and enabling proactive measures. Techniques such as machine learning algorithms for anomaly detection, simulation models, and sentiment analysis from news and social media can help forecast risks related to supply, demand, geopolitical instability, and environmental events. Predictive insights allow firms to diversify suppliers, optimize routes, and maintain buffer stocks, thereby reducing vulnerability. Integrating AI into risk management frameworks also helps in real-time incident response and automated contingency planning. Furthermore, AI tools can facilitate continuous risk assessment by analyzing transactional, environmental, and geopolitical data streams, thus enabling supply chain managers to implement early warning systems and agile responses. Companies can also use AI-driven scenario modeling to evaluate the potential impacts of various disruptions and prepare mitigation strategies in advance.

8. Workforce Transformation and Skill Development

As AI continues to automate routine tasks in supply chains, the workforce must adapt to changing roles that emphasize data literacy, strategic thinking, and collaboration with AI systems. Organizations must invest in upskilling initiatives, AI-literacy programs, and cross-functional training to prepare employees for emerging roles such as AI supervisors, data analysts, and automation coordinators. Human-AI collaboration models will become essential, necessitating a cultural shift toward continuous learning and adaptability. Furthermore, organizations should foster interdisciplinary learning environments where supply chain professionals gain exposure to data science and technology management.

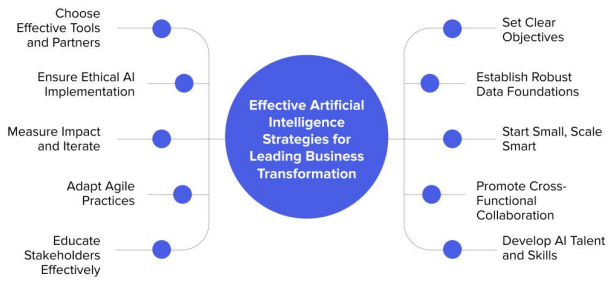

Fig5: AI Strategy Framework

9 . Future Research Directions

9.1 Development of Adaptive AI Systems:

Future research on Artificial Intelligence in supply chain management should delve deeper into the development of adaptive AI systems capable of responding in real-time to volatile market conditions and unstructured data.

9.2 End-to-End Supply Chain Integration:

There is a pressing need for studies that explore AI integration across end-to-end supply chain processes rather than isolated segments.

9.3 Interdisciplinary Technology Synergies:

Interdisciplinary research combining AI with blockchain, IoT, and edge computing could yield synergistic innovations for real-time visibility and traceability.

9.4 Ethical and Social Implications:

Future work should investigate the social and ethical implications of AI-driven automation, especially concerning employment displacement and bias in decision-making algorithms.

9.5 Context-Specific Implementation Challenges:

Researchers should also focus on region-specific studies, particularly in developing economies, to understand context-specific challenges and opportunities for AI adoption.

9.6 Long-Term Impact Assessment:

Empirical studies quantifying the long-term ROI and sustainability impact of AI in supply chains would provide valuable insights for both practitioners and policymakers.

10. Results

In this section, we present the key findings from the literature analysis and case studies, with a focus on the effectiveness and impact of AI adoption in supply chain management (SCM). The results are based on the case studies of Amazon, Maersk, and Siemens, and the analysis of key performance indicators (KPIs).

10.1 Cost Reduction: Companies that have adopted AI technologies report significant cost savings. For instance, Amazon's implementation of AI-driven warehouse automation has reduced operational costs by automating tasks that would otherwise require human labor. Maersk's use of AI for predictive maintenance has minimized costly breakdowns in its shipping fleet.

10.2 Efficiency Improvement: AI has led to a notable increase in efficiency across supply chain operations. Amazon's deployment of Kiva robots in fulfillment centers has boosted picking and packing speed, resulting in faster order processing times and lower lead times. Similarly, AI-driven optimization algorithms have enabled Walmart to reduce inventory levels while ensuring product availability.

10.3 Risk Mitigation: AI-powered demand forecasting systems have allowed companies like Coca-Cola to better anticipate shifts in consumer demand, reducing the risk of stockouts or excess inventory. AI tools also help mitigate supplier risk by providing early warnings of potential disruptions, such as geopolitical events or natural disasters.

These results indicate that AI can effectively enhance the overall performance of supply chains, driving cost reduction, improving efficiency, and mitigating risks**.**

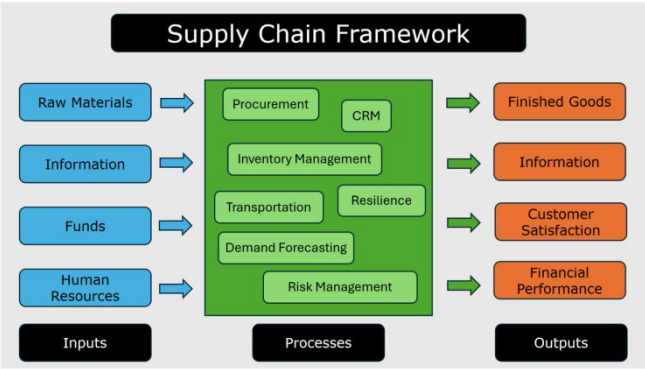

Fig6: Supply Chain Framework

11. Discussion

While AI has shown immense promise in revolutionizing supply chain operations, several challenges must be addressed for its widespread adoption.

11.1 Data Quality: One of the most significant barriers to successful AI implementation is data quality. AI models require vast amounts of high-quality, clean data to produce accurate results. In many cases, organizations struggle to collect and maintain data that meets these requirements. Inaccurate or incomplete data can undermine the effectiveness of AI algorithms.

11.2 Integration Complexity: Integrating AI technologies into existing supply chain infrastructure is another major challenge. Many organizations have legacy systems that are not compatible with advanced AI tools. Seamlessly integrating AI into these systems requires substantial investment in both time and resources.

11.3 Ethical and Privacy Concerns: As AI becomes more embedded in supply chains, concerns about data privacy and ethical implications grow. Companies need to ensure that they are transparent about how AI systems use data and that they comply with privacy regulations, such as the General Data Protection Regulation (GDPR).Despite these challenges, the benefits of AI adoption are evident, and organizations that successfully overcome these obstacles are poised to gain a competitive advantage.

12. Conclusion

This paper has explored the transformative impact of Artificial Intelligence on supply chain management. Through an in-depth analysis of AI technologies, applications, and real-world case studies, we have demonstrated that AI is playing a pivotal role in enhancing efficiency, reducing costs, and mitigating risks within the supply chain.The study highlights several key opportunities for AI in SCM, including demand forecasting, inventory management, and warehouse automation. At the same time, it identifies critical challenges such as data quality, system integration, and ethical concerns that need to be addressed for successful AI adoption. Future research should focus on the development of new models for integrating AI across supply chains, as well as strategies for overcoming the barriers identified in this paper.

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