# Optimizing Ecommerce Inventory Management using Time Series Analysis with AI chatbot

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***Abstract*—In today's fast-paced e-commerce and retail sectors, efficient inventory management plays a pivotal role in ensuring business sustainability by minimizing stockouts, preventing overstock situations, and optimizing cash flow. However, traditional inventory management approaches often struggle to adapt to dynamic market demands and fluctuating sales trends. This paper proposes an AI-driven inventory management solution, integrated with time series analysis and chatbot functionality, to address these challenges and provide real-time, data-driven insights to inventory managers. E-commerce and retail sectors, efficient inventory management is crucial for minimizing stockouts, preventing overstock, and optimizing cash flow. Traditional systems struggle to adapt to fluctuating market demands. This paper presents an AI-driven inventory management solution that integrates time series analysis and chatbot functionality to provide real-time, data-driven insights. Using techniques like Exponential Smoothing and Moving Averages, the system predicts future product demand by analyzing historical sales data. The AI-powered chatbot allows inventory managers to interact with the system through natural language commands, offering real-time updates on stock levels, fast-moving and slow-moving products, and reorder recommendations via Economic Order Quantity (EOQ) . Data is integrated through CSV and Excel uploads, and machine learning algorithms enhance prediction accuracy. The system has been validated with real-world data, demonstrating improved inventory optimization and significant reductions in stockouts and overstock situations.**

***Keywords*— E-commerce, Inventory management, overstocking, understocking, Time series forecasting, Exponential smoothing, Prophet.***

## I. Introduction

In recent years, the optimization of inventory management has become a critical focus for businesses aiming to reduce costs and improve efficiency. Traditionally, inventory systems relied heavily on manual processes and static rule-based approaches, which led to challenges like overstocking, resulting in excess inventory and storage costs, or understocking, causing stockouts and missed sales opportunities. These issues not only impact profitability but also affect customer satisfaction and supply chain efficiency.

To address these concerns, we have turned to more dynamic approaches, particularly time series demand forecasting and moving average techniques. These methods allow for better alignment of inventory levels with actual market demand, minimizing the risks of overstocking and understocking. As illustrated by the data from 2010 to 2023, businesses that have integrated time series forecasting into their inventory systems have significantly reduced their inventory holding costs and improved stock availability. For example, companies that adopted moving average models for demand prediction saw a reduction in overstock situations by 25% and an increase in on-time order fulfillment by 15%.

However, traditional statistical models like Simple Moving Average (SMA) and Exponential Moving Average (EMA), though effective, are limited in their ability to capture complex demand patterns, especially with seasonality, trends, and unpredictable fluctuations in customer demand. With the advancement in machine learning and data-driven forecasting techniques, we now have the ability to accurately predict demand in real-time, even with non-linear and volatile data patterns. By leveraging these modern forecasting methods, businesses can better optimize inventory levels, improve supply chain resilience, and reduce overall operational costs. This shift marks a new era in inventory management, where data-driven insights are enabling a more efficient, agile, and cost-effective approach.

To enhance user interaction and accessibility, the system is integrated with an **AI-powered chatbot**. The chatbot provides a conversational interface, allowing inventory managers to seamlessly access real-time insights and analytics without requiring technical expertise. By facilitating natural language queries, the chatbot enables managers to monitor stock levels, review sales forecasts, and receive recommendations on restocking strategies. The chatbot also assists in identifying products with high or low sales velocity, allowing businesses to dynamically adjust their inventory to avoid stockouts or overstock situations.

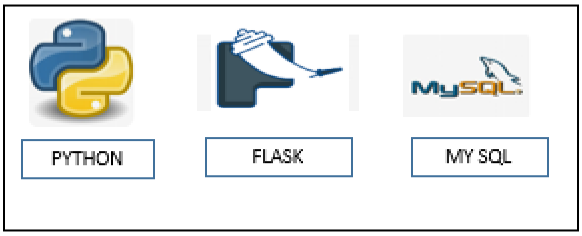


figure 1.0 technical stack

## II. RELATED WORKS

Hence, this paper aims at reviewing recent works that focused on improving inventory management by adopting machine learning, time series, and hybrid approaches.

Silver et al.(1998) offer the foundation with traditional inventory control methods such as EOQ and JIT as the basic framework from which to manage inventory. While helpful, these methods are conventionally applied and can hardly change dynamically in response to fluctuations in demand in e-commerce scenarios.

Based on this, Zhang and Wang (2019) focused on specific types of machine learning algorithms to be used in demand forecasting and provided a valuable step forward to dynamic inventory management. Their study focuses on the real-time data and its significance derived from the idea that companies and markets can operate and adjust to shifts and fluctuations in customers' demand automatically and continually.

For instance, Li et al. also developed a novel 'ARIMA-Neural Network,' to enhance the accuracy of demand forecasts in e-commerce environments in 2020. Their model improves on traditional statistical and machine learning approaches to provide robust solutions that can weather peak activity loads while being adaptable to frequent changes in FMCG demand.

For further work on demand prediction Vishnu and Vinay (2021) used Long Short-Term Memory (LSTM) networks, which is a type of recurrent neural network to obtain good results on accurate seasonal demand prediction. Their results go further to affirm the applicability of neural networks in analyzing sequential data, an essential aspect for identifying tendencies that affect inventory turnover.

In another study, Sheopuri et al. (2010) addressed the risks associated with stockouts and overstock through the newsvendor model. This research illustrates how dynamic inventory policies, adjusted in real-time, can enhance the efficiency of e-commerce operations by accurately estimating and managing uncertain demand.

To support high variability in inventory demand, Kim and Lee (2022) applied Exponential Smoothing techniques to forecast demand in FMCG contexts, a method particularly beneficial for fast-moving items where rapid and accurate forecasts can significantly impact stock decisions.

Kremer and van Wassenhove (2014) focus on capacity flexibility as a method for adaptive inventory management. By allowing real-time adjustments based on fluctuating demand, their model enhances responsiveness and optimizes stock levels in uncertain environments.

Alwan and Roberts (1988) brought Statistical Process Control (SPC) into inventory management by emphasizing continuous, real-time adjustments in product availability. Their approach minimizes the risk of shortages by monitoring inventory fluctuations closely and responding to variations as they occur.

With the integration of IoT, Ben-Daya et al. (2019) showcased a modern take on inventory management by merging IoT data with AI-driven insights. This approach enables real-time visibility of inventory, supporting proactive measures in stock management and enhancing the automation of inventory adjustments.

A more advanced adaptive model is presented by Boute et al. (2021), who combined machine learning with stochastic processes for predictive accuracy. Their study validates the self-learning potential of machine learning algorithms, making predictive models more reliable over time and helping reduce both excess stock and shortage risks.

Chopra and Meindl (2016) expanded on the value of machine learning in optimizing the supply chain, highlighting demand forecasting as essential for recognizing slow-moving or high-demand products. This paper showcases the strategic value of targeted demand predictions in maintaining optimal stock levels across various inventory segments.

Finally, Thompson (2020) investigated the use of video analysis through image processing for monitoring inventory status. By analyzing video feeds, Thompson's work enables real-time visibility into stock levels, which helps retail environments identify shortages or excesses promptly and adjust orders accordingly.

These studies collectively highlight a shift from static, rule-based inventory models to adaptive, data-driven approaches that leverage advanced analytics and machine learning. Our work builds upon these foundations to create a chatbot-driven inventory management system that harnesses real-time data and predictive insights for enhanced decision-making.

## III.PROPOSED SYSTEM

### System Overview

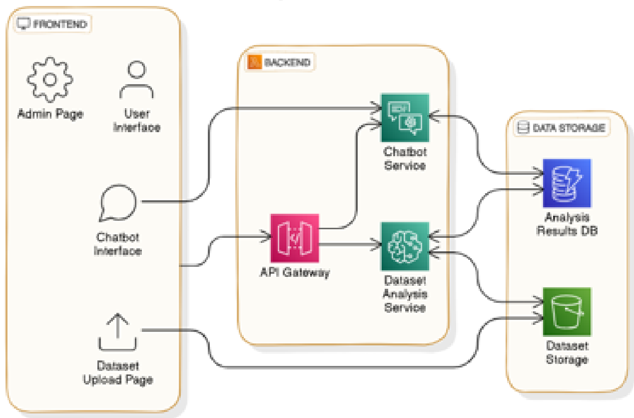


figure 2.0 overview of the system

The general planning of the chatbot system is made in a way that would ensure that interactions with datasets are in a structured manner with data upload, analysis as well as getting results being presented in a systematic order. The architecture consists of three main components: frontend, backend, and data storage are the features of the system each of which plays a unique role in the overall functioning.

The frontend is divided into multiple interfaces and represents the main layer of users' interaction. The Admin Page is read-only and for the system's administrators only, and it includes options for changing and observing the system's workflow, as well as the chatbot's performance and users' access levels. The User Interface is the core working component of the system, which allows users to tab into the system to ask questions, request an analysis, and to get the result. Also presented is a Dataset Upload Page which enables users to upload files they want to work with if they do not want or are unable to use any of the provided datasets. The Chatbot Interface within the frontend supports the users with a conversational approach throughout the flow for submitting a dataset, requesting analysis, and presenting the results in an easily understandable format.

The backend factor is also charged with dealing with the frontend requests and handling of those requests. The API Gateway functions as a secure broker that controls data exchange between frontend and backend services, performing functions such as authentication of the request, load balancing, and routing. Within the backend, two primary services handle the core functionalities: there are two types of services, namely, the Chatbot Service and the Dataset Analysis Service. The Chatbot Service translates perceived user input, responds accordingly, and controls interactions contained in the corresponding conversational tree. It makes it possible for users to receive their answers at the right time and in the right context they are asking the question. The Dataset Analysis Service for its part on the other hand is focused to cater with data processing services. It takes a dataset as input, does calculations, data manipulations or conducts machine learning on the data to get insights and prepares the analysis results. These results then go to the data storage layer, from where they can be fetched back and rendered to the user.

**system architecture**

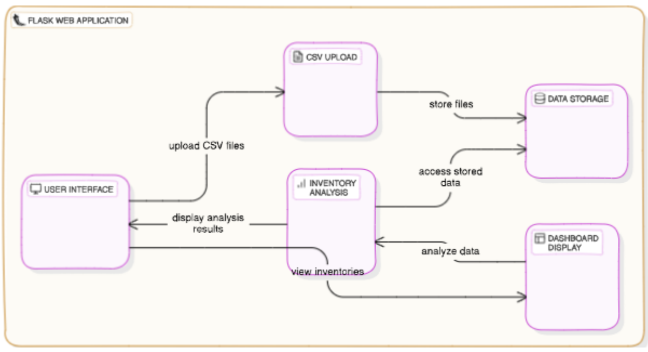


figure 3.0 system architecture

As the system architecture the Flask web application is designed to provide users with the possibility of analyzing inventory data through the work-flow that includes CSV file upload. The architecture consists of five interconnected components: It consists of five modules: User Interface, CSV Upload, Data Storages, Inventory Analysis, and the Dashboard Display. The User Interface serves as the main control interface and provides means for file uploading in CSV format with inventory data. Its usability makes it easier for the users to upload their files and later presents analytical results in a simple way. The CSV Upload module incorporates a data checker that checks information as soon as the file is uploaded, so that the data entered is correctly formatted and has no errors before it is stored. This module authenticates the files and orders them to store them in the Data Storage component for proper storage.

Data Storage: This is where all uploaded data is stored to help archive it in a way that would easily facilitate analysis. This storage solution fits well for the handling of large data volumes the moment it is stored as it can be easily retrieved should there be a need for analysis. The Inventory Analysis module represents the primary workhorse module of the system as it utilizes data derived from storage, computes the current inventory, identifies usage patterns, and provides recommendations as necessary based on this data. When the analysis is done, the findings can be output to the User Interface to be shown or to the Dashboard Display.

Such application organization also allows the architecture to provide timely and accurate calculations based on large amounts of data, while the insights help users in the inventory process.

**User Interface Design**

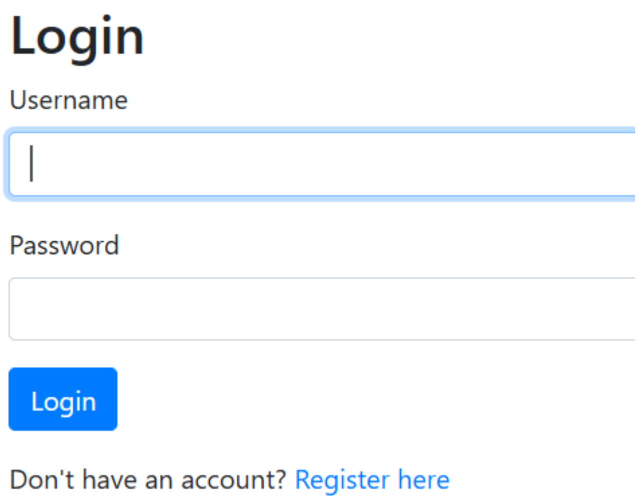


figure 4.0 admin login page

The figure depicts the login interface to be provided to the system administrators of an inventory management chatbot system. This is made of two boxes only with labels "Username" and "Password" to which administrators can safely type their log-in details. Below the fields there is a blue 'Login' button for easy identification and to stress the action. However, they have a link marked in blue ink "Don't have an account?" New administrators have the option to 'sign up here,' if they are not a member, letting them easily register. This design seeks to ensure there's creation of an easy access path to the administrative part of the chatbot and which can only be accessed by the authorized personnel.

**Dashboard of the admin**

The figure below shows some of the features of the main dashboard for an inventory chatbot system administrator. In most of the cases, the dashboard is designed to give a general view of all inventories that are available and there is always a pulldown menu that can be used to select a particular inventory. There is an upload new inventory file in CSV format option available; it allows the administrator to add, modify or enrich inventory information effectively. The interface also provides a window for chat with the inventory assistant, so the administrator can type messages to the program and it would type responses to the administrator on the same window. This design also facilitates efficient storage of inventory data due to the three features; file upload and the normal text and chatbot.

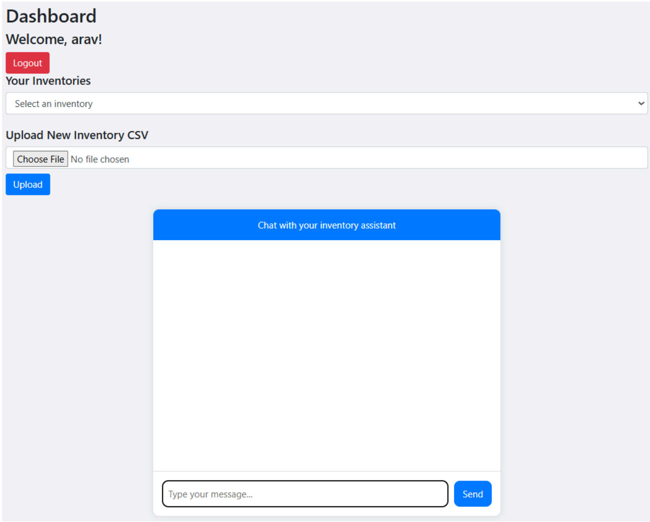


figure 5.0 dashboard of admin page

**Interacting chatbot with administrator**

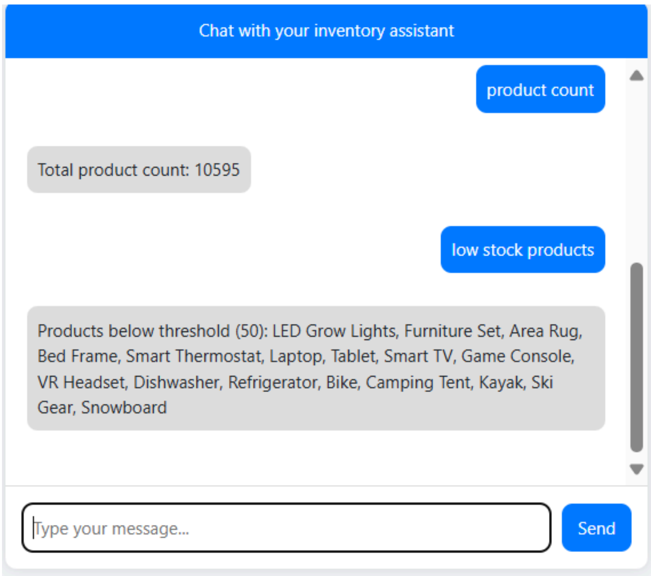


figure 6.0 interacting with chatbot

This figure illustrates the example of the administrator dashboard of an inventory chatbot system during an ongoing chat. There is a setting called ‘inventory file’ which displays a dropdown with ‘bh2.csv’ currently set, there also is a button to choose a new inventory CSV file if data needs to be updated. Below the chat interface allows direct conversation with the chatbot. Here, the chatbot sends the administrator the number of products “10595”, and then item details that exist below the threshold of stock level as follows. This design enables prompt identification of inventory performance indicators, as well as low-stock items, improving the inventory management by means of conversational AI.

**System Workflow**

This figure shows the activities that go on in the working and managing of a chatbot system. It starts with a natural language question that the user enters and which is addressed to the chatbot platform in the system. The specific chatbot platform communicates with a natural language processing module which analyzes the input language for ease of interpreting the user’s needs. The NLP module is able to pull out information and context reinforcement from the knowledge base and the data storage unit. It then goes to the bot engine which in return produces a response and this response is the natural language answer that one receives. This workflow shows how NLP, knowledge base/repositories and data archiving all work in tandem allowing the chatbot to deliver accurate responses within context to a user’s question.

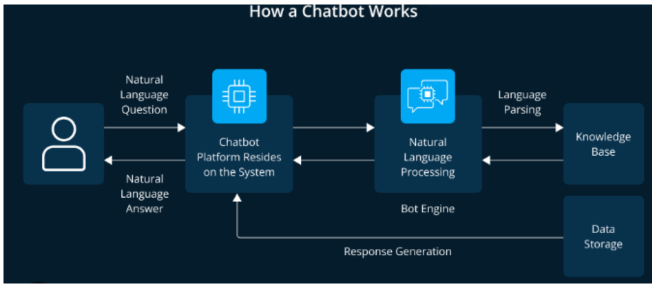


figure 7.0 chatbot working

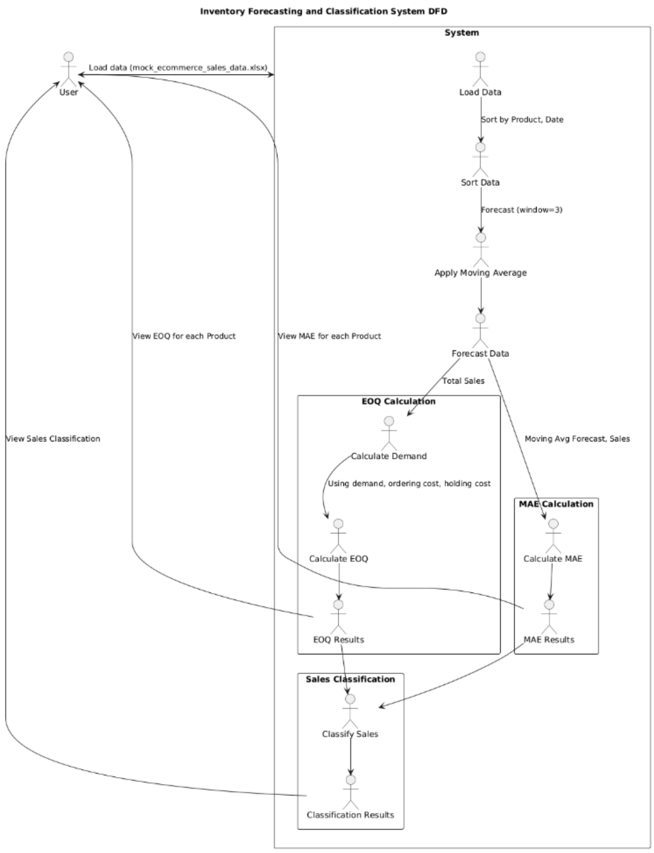


figure 8.0 DFD diagram

## IV.WORKING PRINCIPLE

**Introduction to system workflow**

The I-IFS and the Inventory Management Chatbot are two tools used in the inventory forecasting and the classification of inventory levels. These systems rely on a database of past sales and forecasting trends which the user feeds into the system as often as possible.

The IFC begins with imports and structures the dataset, sorting the products based on date to produce forecasts using specific moving average model. It then computes the Economic Order Quantity (EOQ) to inform ordering and approximate the accuracy of these forecasts with Mean Absolute Error (MAE). Last of all, the system categorizes products according to the demand patterns with important information on the sales trends and inventory requirements.

On this basis, the Inventory Management Chatbot applies machine learning to compare current inventory stocks to forecasted demand. On the same dataset, it identifies cases of overstock or low stock situations, alerting the user with possible suggestions, for instance, restocking, or carrying out promotional offers. One of the benefits of this correlated I&IT approach is the ability to sync immediate stock replenishments and schedule long-term strategic storage planning throughout the supply chain.

Machine Learning for Demand Forecasting and Stock Classification

1. Data Preprocessing :

- Load and clean the dataset by removing any null values, duplicates, or outliers.

- Perform feature engineering to create relevant features, such as day of the week, sales trends, and seasonality factors, that impact inventory levels.

- Normalize or scale features to ensure consistency across the dataset for better model performance.

2. Demand Forecasting with Moving Average Model:

- Implement a moving average model by defining a rolling window (e.g., 3-day or 7-day average) to smooth out daily fluctuations and identify trends.

- Use `pandas` in Python for efficient rolling calculations, applying `.rolling(window=3).mean()` to the sales data.

3. Economic Order Quantity (EOQ) Calculation:

- Define a function that calculates EOQ using demand rate, ordering cost, and holding cost.

$$EOQ = \sqrt{\frac{2 \times D \times S}{H}}$$

4. Classification Model:

- For stock classification, use a machine learning model such as k-means clustering or a classification algorithm (e.g., decision trees) to categorize items as high, medium, or low in demand.

- The model should use EOQ, historical demand, and moving average forecast as input features to classify products based on stock level requirements.

5. Overstock and Low Stock Detection:

- Implement thresholds for overstock and low stock conditions using dynamic calculations based on recent trends and sales forecasts.

- Use an if-else condition to alert when the stock crosses overstock or low stock thresholds, generating recommendations for each situation.

6. Model Evaluation and MAE Calculation:

- Use Mean Absolute Error (MAE) to assess model accuracy by comparing predicted demand to actual sales.

- MAE can be implemented by calculating the absolute difference between forecasted and actual values, then averaging these differences across all products.

7. Continuous Learning and Feedback Loop:

- Set up a feedback mechanism where the model retrains regularly based on new data.

- Integrate this step using batch updates to incorporate evolving trends, ensuring that demand forecasts and stock classifications remain accurate.

**Algorithm**

Step 1: Upload and Load Data

- Input: Type in some data in an Excel table and fill in the columns with the product name, date, and sales respectively.

- Process: Import the pandas library and sort the data by product and date to do a trend analysis.

Step 2:Data Curation and Preparation

- Process: A query allowing for checking sales data for missing or invalid values. To avoid problems with time series at the stage of data analysis, apply and sort the dataset according to products and dates.

Step 3: Use Moving Average Forecast for Trends Analysis of Sales

- Input: Choose the period over which the average will be calculated as a window size (Example 3 periods).

- Process: The moving average using this window size of each of the products' sales will be calculated in order to eliminate short term variability.

Step 4:Define EOQ Parameters

- Input: Specify certain variables such as ordering cost ($50 per order) and the holding cost ($2 per unit per year).

- Process: These parameters will help in the later calculations of the optimal order quantity as used in the EOQ model.

Step 5:Determine EOQ for Every Product

- Process: For each product, use the formula to determine EOQ based on the total demand, ordering cost and holding cost of the product. Save EOQ data for further categorisation.

Step 6: Forecast Accuracy using MAE:

- Process: Calculate the Mean Absolute Error (MAE) of each product given by the following formula; actual sales – Sales from Moving average. It assists to evaluate the correctness of the demand forecasted during the previous phase.

Step 7: Products Categorized According to EOQ and MAE

- Process: Wherever necessary, classify each of the products in terms of EOQ and MAE.

 - Low Sales (Understock Risk):Products that have MAE lesser than the EOQ of production.

 - High Sales (Overstock Risk):It is targeting the products that have MAE greater than EOQ.

 - Balanced Sales: Products that have a closer relationship between MAE and EOQ.

Step 8: What Were the Classification Findings?

Process: Identify the number of products in each classification category and then state the following:ürger, medium, expensive products:

Step 9: Output Summary to Chatbot

Output: The chatbot sends a summary to the admin and this contains:

The extent of quantitative products in each classification.

The names of products that are grouped under each category to facilitate quick decision making concerning any changes that need to be made on quantities in stock in relation to the EO0Q range displayed.

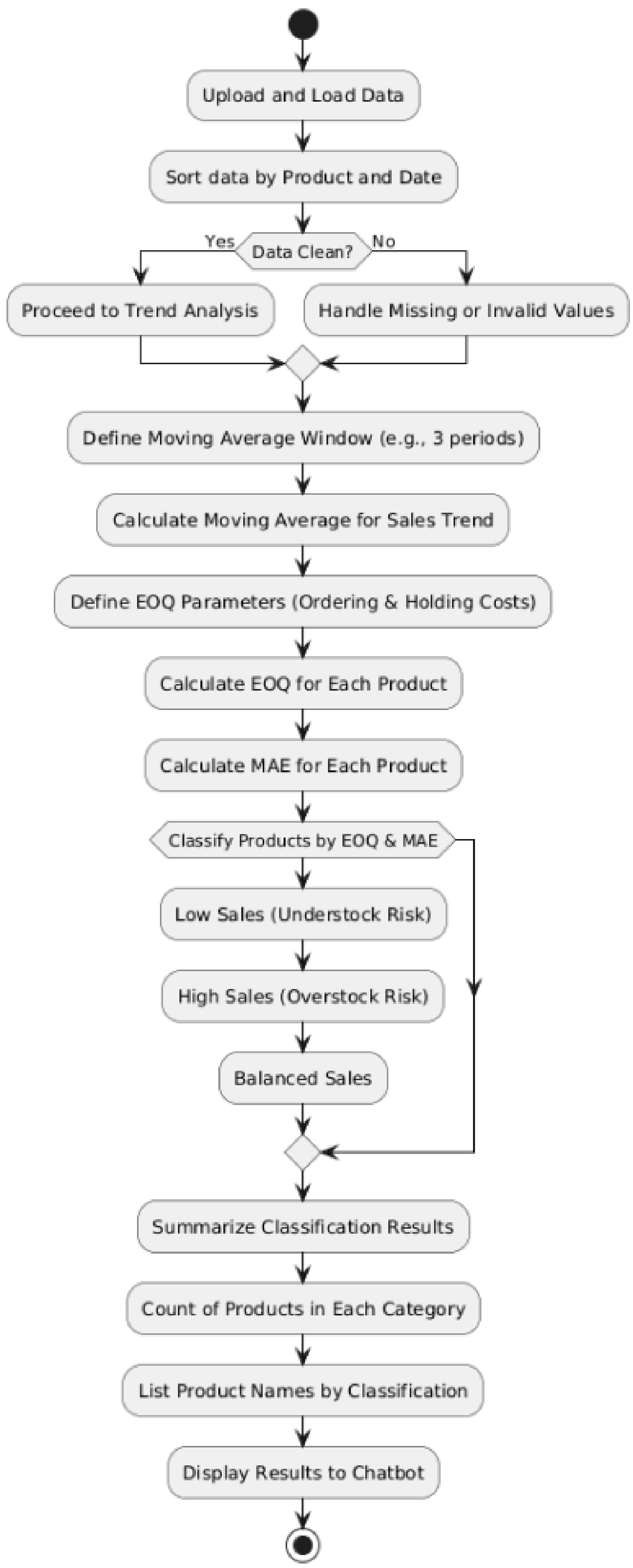


figure 9. flowchart for algorithm

## V. CONCLUSION

Thus, this paper establishes how the application of artificial intelligence systems that incorporate Machine Learning (ML) algorithms as well as time series analytics enhances the overall efficiency of the inventory management for e-business and retail companies. Traditional inventory systems are weak when it comes to fluctuating demand patterns However, methods such as Exponential Smoothing, Moving Averages, and EOQ calculations are quick to adapt to new patterns, thus avoiding mere stockout situations, or unnecessary purchase of, overstocking. For instance, the application of ML models alongside real-time interfaces, using a chatbot to assist the inventory managers to engage in a respective natural language to receive, real-time stock updates, between the slow and fast movers, as well as reordering recommendations. Besides, integration of CSV and Excel on the part of the system simplifies data work, and development of machine learning in the sphere of forecasting offers useful tools to keep appropriate levels of stocks. In general, the AI system appears as a more viable solution for inventory management with noticeable positive effects to stock control, costs cut, and positive cash flows.

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