# AI Projects with Python Midterm

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**PROJECT TITLE:** Solution for Dead stock problem

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# Executive Summary

## Brief Summary

Dead stock refers to products not selling for long periods of time. These items consume storage space that could otherwise be used for other items. This can be quite costly, because of warehouse management expenses.

The solution we have is an AI-Powered Dead Stock Risk Prediction System which analyzes performance of the product, sales history, market trend, and inventory levels to generate a risk score for the products we have at hand:

The proposed solutions are expected to generate significant business benefits by reducing dead stock levels, improving cash flow efficiency, and optimizing demand management. By minimizing unsold inventory, the company can free up tied capital, mitigate financial losses, and support healthier long-term growth.

# Problem Analysis

## What is Dead stock?

Dead stock consists of products that do not generate sales within a reasonable time. These items accumulate in warehouses, create unnecessary storage costs, and often need to be sold through discounts or disposed of entirely.

## Why is Deadstock a Critical Problem?

Deadstock restricts cash flow and limits companys available cash flow. This leads to a decline in profits and negatively impacts the company's financial performance because:

- Warehouse costs increase: Products that remain in storage for a long time increase warehouse costs.

- Discount losses: Products remaining in the warehouse are sold at a loss with excessive discounts.
- Operational inefficiency: storage, warehouse tracking and returns become difficult

### Current Challenges in e-commerce:

E-commerce companies experience dead stock problems due to unpredictable trend changes and excessive variety.

### Scale and impact of the problem:

Many e-commerce companies worldwide are experiencing multi-million dollar product deadlock. This slows down operations and disrupts product flow.

# Proposed AI Solution

### How does your solution work?

The proposed AI system is designed to detect the "dead stock" problem encountered in e-commerce businesses at an early stage, highlight risky products, and develop appropriate strategies. The system generates a Dead Stock Risk Score for each product and determines which products are at risk of not being sold in the future.

1)Data Collection and Feature Engineering: Sales records, inventory levels, pricing and discount history, product attributes, and user behavior data are collected from multiple sources. These datasets transformed into meaningful features that can be used as model inputs. Such as: Sales velocity Stock age Click-through rate (CTR) Add-to-cart but not purchased rate Seasonality or period information Discount history

2)Predictive Modeling and Risk Score Generation: Machine learning models analyze patterns in historical data to predict the likelihood of a product becoming discontinued. For each SKU, the model generates a Dead Stock Risk Score between 0 and 1. The higher the score, the higher the risk of the product becoming dead stock.

3)Decision Support and Automatic Actions: The scores produced by the model are evaluated by a decision engine that supports strategic decisions:

- Highlights risky products
- Suggests dynamic pricing/discounts
- Generates special coupons for customers
- Alerts category managers
- Triggers a "small-lot stocking" strategy for new products
- This increases operational efficiency and significantly reduces dead stock.

## What AI/ML techniques would you use?

1)Supervised Learning Models: These models predict the likelihood of products going unsold in the future by looking at past sales and inventory data. -Random Forest -XGBoost -Logistic Regression (baseline model) These models provide both high accuracy and ease of understanding for business units because they can explain feature importance.

2)Time Series Forecasting Models: -LSTM (Long Short-Term Memory) or Prophet -Effective for predicting future sales trends -Useful for detecting seasonal patterns and sudden demand changes

3)Reinforcement Learning (Optional Advanced Phase): -Can optimize discount strategies based on customer response -Learns which incentive level maximizes sales with minimum margin loss

4)Recommendation Algorithms: -Personalized advertising and coupon targeting -Collaborative filtering or deep learning–based recommendation models -Helps display high-risk items to the right customers

## What data would be needed?

The system requires a combination of sales, behavioral, and product metadata to ensure accurate predictions.

**1)Sales & Inventory Data**

- Historical sales quantity (daily/weekly)
- Stock levels and stock age
- Sell-through rate
- Price changes and discounts
- Return rates

**2)Product Information**

- Category, brand, seasonality
- Product type
- Release date
- Cost and profit margin

**3)Customer Interaction Data**

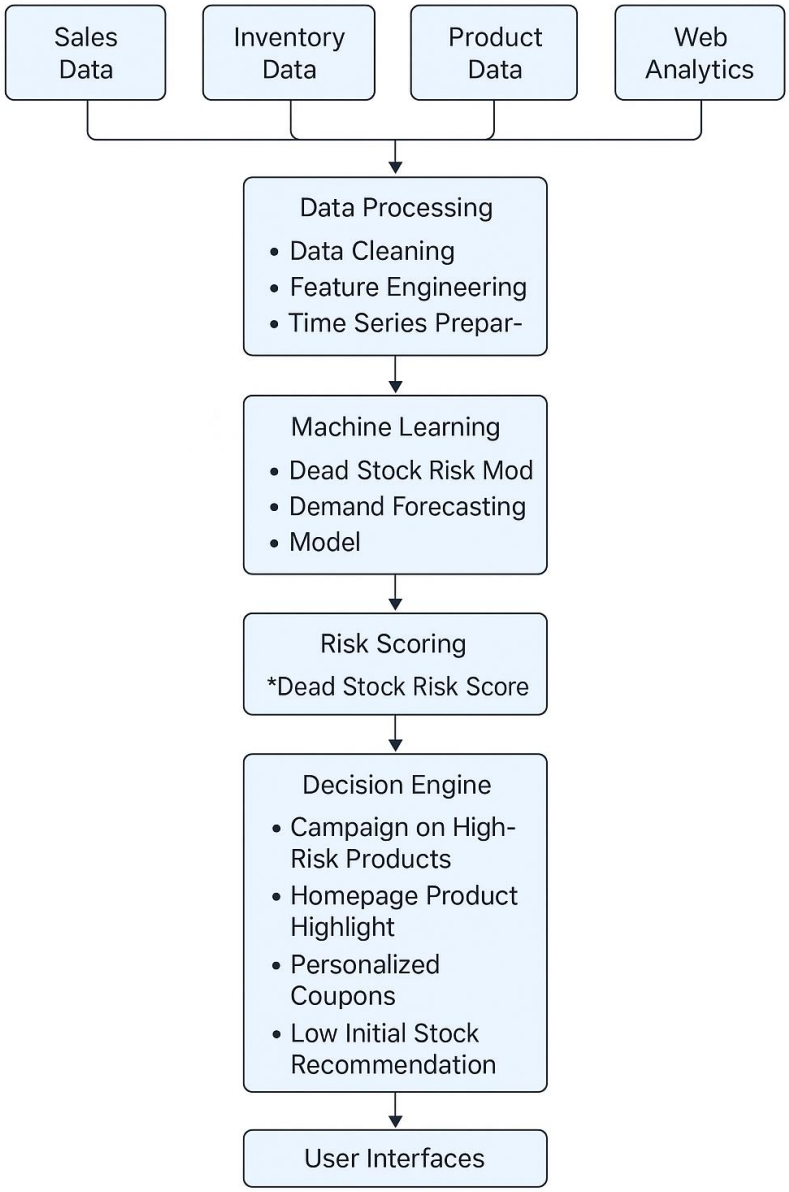
- Page views, click-through rate
- Add-to-cart but not purchased events
- Bounce rate
- Conversion rate
- Customer segmentation

**4)Operational & Supply Chain Data**

- Supplier lead times
- Delivery delays
- Warehouse handling time
- Packaging or restocking costs

These data points enable the model to detect which products are slowing down, losing relevance, or failing to convert browsing customers into buyers.

## System architecture diagram




# Proposed AI Solution(Technical Feasibility)

### Technology stack

- **Python Libraries:** Pandas, NumPy, Scikit-Learn,
- **Backend API:** FastAPI
- **Deployment:** Streamlit or Gradio
- **Database:** MsSQL
- **Visualization:** Matplotlib, Seaborn

### Implementation approach

1. Data is taken from e-commerce system.
2. Feature engineering is done (sales velocity, demand trend, stock turnover, etc.).
3. Train the machine learning model.
4. Deploy the model using an API.
5. Visualize risk scores.

### Data pipeline architecture

Raw Data → Cleaning → Feature Engineering → Model Training → Risk Prediction → Dashboard

### Scalability considerations

- It can be scaled horizontally with its microservice architecture.
- The model can be retrained regularly.
- Spark integration is possible for big data.

### Integration with existing e-commerce systems

- It can be connected to existing inventory management software via API.
- The dashboard serves as a decision support system for managers.

### Expected performance metrics

- Accuracy: %80+
- F1 Score: %0.70+
- ROC-AUC: %0.85+

# Business Impact & Implementation

### Expected operational improvements

AI-based dead stock risk prediction system will provide measurable improvements in operational processes.

- Since risky products are identified early, stock planning is done more accurately.

- Unnecessary storage time is reduced.

- Adjustment of supply quantities is achieved more evenly.

## Cost-benefit analysis

The cost–benefit analysis shows that the proposed AI solution provides high operational savings and financial gains compared to the low development cost.

**Costs:**

- AI model development and integration costs

- Data collection and data cleaning process

- Dashboard and alert system development

- Team training costs

**Benefits:**

- Reduction in dead stock

- Savings in warehouse space

- Cost reductions in purchasing units through better demand forecasting

- Savings in operating hours through automatic reporting

## Customer experience benefits

AI solutions not only provide operational benefits but also significant improvements in the customer experience:

- Increased product availability
- Speeds up operational flow by eliminating unnecessary product clutter in the warehouse
- More accurate pricing
- Increased user confidence
- Cleaner inventory data for better recommendation algorithms

## Implementation challenges and solutions

**Data scarcity / corrupted data:**

- In e-commerce companies, SKU (stock keeping unit) history may not always be clean.

Solution: Create a data cleansing pipeline and use imputation techniques for missing data.

**Cross-department integration:**

- Purchasing, warehouse, and marketing processes need to work together seamlessly.

Solution: Provide API-based integration and develop a common dashboard for all teams to use.

**Model accuracy concerns:**

- Inaccurate predictions can negatively impact operations.

Solution: Establish A/B testing, regular model retraining, and performance monitoring mechanisms.

A/B Testing : compares the performance of two content versions to see which one is more appealing to visitors/viewers

**User adoption:**

- It can take time for teams to gain confidence in AI output.

Solution: Offer training programs and a demo environment.

## Return on investment projection

The AI-supported dead stock prediction system provides financial returns in a short time after implementation.

Estimated 1-Year ROI (Return on Investment):

Dead stock reduction: 20–35%

Annual storage cost savings: 10–18%

Reduction in losses due to promotions and discounts: 20–30%

Operational labor efficiency: 8–12% automation savings

Estimated annual ROI (Return on Investment): 120–200%

Based on these projections, the system fully pays for itself within the first year and transforms the company into more efficient.

# Conclusion & Future Work

### Key takeaways

This project provides a scalable, applicable, and high business impact solution to solve the dead stock problem with artificial intelligence.

### Next steps for implementation

- Training the model with real data
- Going live with the Dashboard
- Completion of API integrations

### Potential expansions

- Adding the demand forecast model
- Automatic campaign suggestion system
- Dynamic price optimization