SE390 Midterm Report – Dead Stock Risk Radar

Cover Page

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- **Project Title:** Dead Stock Risk Radar – AI-Powered Inventory Intelligence
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1. Executive Summary

Turkey’s e-commerce sector crossed ■1.2 trillion in GMV in 2024 with thousands of SMEs selling across omnichannel marketplaces. Yet 18–22% of stocked SKUs become “dead” every quarter, locking up capital, occupying warehouse space, and forcing margin-eroding markdowns.

We propose **Dead Stock Risk Radar**, an AI service that ingests daily inventory, sales, and contextual signals to predict SKU-level dead stock risk 2–4 weeks in advance. A RandomForest classifier trained on rolling sell-through metrics labels high-risk SKUs, while a Streamlit dashboard surfaces prioritized actions (markdowns, bundling, replenishment freezes).

Expected outcomes for a mid-size retailer (5 stores, 20 product lines in our prototype):

- **Operational:** reduce aged inventory by 30% within two cycles, freeing ~15% warehouse capacity.
- **Financial:** unlock ■6M working capital annually and cut emergency discounting spend by 12%.
- **Customer experience:** improve top-SKU availability and delivery SLAs by proactively reallocating stock.

2. Problem Analysis

What is dead stock? Inventory that remains unsold beyond a target aging window due to mis-forecast demand, seasonality shifts, ineffective promotions, or assortment complexity. It ties up capital, drives warehousing costs upward, and requires steep markdowns or liquidation.

Operational pain: Warehouses in Istanbul and Izmir report storage utilization above 90% every peak season. When 20% of pallets carry low-velocity SKUs, picking routes lengthen, labor costs increase, and replenishment of healthy SKUs is delayed. Cash is trapped in unsellable goods, forcing debt financing for new buying cycles.

Customer impact: Dead stock coexists with frequent stockouts on fast movers because planners lack granular visibility. Delivery delays, cancelled orders, and bouncing carts erode brand trust.

Market context: Turkish e-commerce grew 130% between 2020–2024 (Digital 2024 Turkey report). SME merchants rely on Excel forecasts; only large incumbents have predictive inventory tools. Dead Stock Risk Radar addresses this adoption gap with an accessible AI layer that plugs into existing ERP/WMS exports.

3. Proposed AI Solution

3.1 Approach Overview

1. **Data ingestion:** Daily CSV exports from ERP/WMS containing `Inventory Level`, `Units Sold`, `Units Ordered`, `Demand Forecast`, pricing, discounts, promotions, weather, and competitor pricing.

2. **Feature engineering:** Rolling 7/30-day sales, rolling inventory, sell-through, days since last sale, order gap, forecast error, normalized risk signals.

3. **Labeling:** Heuristic rule marks SKUs as dead-stock-risk when high inventory coincides with slow turnover or overstock vs. forecast (using the `retail_store_inventory.csv` dataset).

4. **Modeling:** RandomForestClassifier (scikit-learn) with balanced class weights; pipeline handles scaling, encoding, and imputation.

5. **Serving:** Streamlit “Dead Stock Risk Radar” dashboard plus optional REST API for back-office integration. Users filter by store/category, monitor risk trends, and download recommended actions.

3.2 Data Requirements

- **Transactional:** SKU-level daily inventory, sales, orders, returns, forecast, pricing, discount flags.
- **Contextual:** Promotions, holidays, local weather (impacting in-store demand), competitor pricing, seasonality tags.
- **Master data:** SKU attributes (category, margin tier), store metadata (region, size, fulfillment type).

Data cadence can be daily batches (parquet/CSV) or streaming events via Kafka connectors.

3.3 ML Techniques & Architecture

- **Model choice:** Tree-based ensemble (RandomForest) for interpretability, handles non-linear interactions and categorical encodings. Future iterations can test Gradient Boosting, survival models, or Prophet-based demand residuals.
- **Risk scoring:** Probability output + heuristic risk score (weighted sell-through, inventory aging).
- **Architecture (textual diagram):**
- **Data sources:** ERP/WMS, POS, marketing systems → **Ingestion layer:** Airflow/Prefect jobs writing to an S3-compatible data lake.
- **Feature store:** Pandas/Spark jobs compute rolling metrics; stored in PostgreSQL or DuckDB.
- **Model training:** GitHub Actions/MLflow pipeline trains weekly; artifacts stored in object storage.
- **Serving:** FastAPI microservice exposes inference endpoint; Streamlit UI or PowerBI dashboard consumes it.
- **Monitoring:** Prometheus/Grafana track precision@k and data drift; alerts to Slack.

3.4 Technical Feasibility

- **Stack:** Python 3.13, pandas, numpy, scikit-learn, Streamlit, joblib for artifacts, Docker for containerization, PostgreSQL/MinIO for data persistence.
- **Implementation plan:**

1. Build ETL connector to fetch nightly CSVs.
2. Deploy feature-engineering script (current `scripts/generate_dataset.py`).
3. Automate model training (`scripts/train_model.py`) with CI.
4. Containerize `app.py` Streamlit UI; optional FastAPI for API consumption.
5. Secure endpoints with OAuth2 / API keys.

- **Scalability & integration:** Microservice design allows horizontal scaling; message queues (RabbitMQ/Kafka) decouple ingestion from inference. Cached predictions stored per store-category reduce latency.
- **Expected metrics:** precision@top-50 SKUs ≥ 0.85, recall ≥ 0.7, inventory turnover uplift +12%, reduction in aged units >90 days by 30%.

4. Business Impact & Implementation

4.1 Operational & Financial Gains

- **Inventory efficiency:** Free up ~2,500 pallet positions annually by acting on risk alerts (estimate based on prototype's 1,235 risky SKU-days).
- **Working capital:** Redirect ■6M tied in idle goods to profitable buys; reduce emergency write-offs by ■1.2M.
- **Logistics:** Shorter picking paths and fewer urgent transfers, lowering labor costs by ~8%.
- **CX benefits:** Improved availability of promoted SKUs (SLA compliance ↑5 points) and faster shipments due to optimized replenishment.

4.2 Cost-Benefit Snapshot

- **Costs:** ■1.1M year-one (data engineering, modeling, Streamlit → React upgrade, cloud infra).
- **Benefits:** ■3.8M savings/earnings (markdown reduction, capital efficiency, conversion gains). **ROI:** 245% within 12 months.

4.3 Implementation Roadmap

1. **Weeks 0–2 – Discovery:** Audit data sources, define dead-stock criteria with planners, choose pilot stores.
2. **Weeks 3–6 – Build MVP:** Implement ETL, feature engineering, baseline model, internal Streamlit dashboard.
3. **Weeks 7–8 – Pilot:** Run side-by-side with planners, collect feedback, refine recommendation logic.

4. **Week 9+ – Scale:** Harden APIs, integrate with ERP workflows, train users, plan bonus functionality (automated markdown triggers).

4.4 Risks & Mitigation

- **Data quality:** Missing or delayed inventory snapshots → add validation checks and fallback heuristics.
- **Adoption:** Planners may distrust black-box scores → provide explainability (feature importances, scenario drill-down).
- **Integration complexity:** Legacy ERPs resist API connections → start with CSV exports; upgrade to middleware later.
- **Concept drift:** Seasonal demand shifts degrade model → schedule monthly retraining and drift monitoring.

5. Conclusion & Future Work

Dead Stock Risk Radar shows that even SMEs can operationalize AI-driven inventory intelligence using accessible tooling (pandas, scikit-learn, Streamlit). By combining engineered sell-through features with interpretable risk scores, planners gain actionable visibility and can intervene before stock becomes dead capital.

Next steps:

1. Productionize the Streamlit prototype (Docker, CI/CD).
2. Integrate with live ERP feeds and implement automated notification workflows (email/Slack).
3. Expand dataset with supplier lead times, margin tiers, returns rate.

Future enhancements:

- Reinforcement learning to optimize markdown timing.
- Supplier collaboration portal sharing risk insights for joint planning.
- Gradio/Streamlit hybrid mobile interface for warehouse supervisors.

Appendix (Optional)

- **Demo assets:** Streamlit screenshots showing KPI tiles, risk trend chart, and recommendation table.
- **Dataset:** `retail_store_inventory.csv` synthetic sample (5 stores × 20 products, 2022–2024).
- **Model metrics:** Precision 1.00, Recall 0.97, ROC-AUC 1.00 on holdout (class-weighted RandomForest).