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FULL PAPER

Using AI Techniques to Forecast Agricultural Commodity Export and Import Volumes Case Study: Grain Silos – Al-Gedaref State

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Abstract

The storage of crops is considered one of the fundamental pillars upon which the Sudanese economy relies. Proper storage ensures the availability of strategic reserves. Given the challenges of monitoring crops under traditional systems—which increases the risk of crop spoilage—it has become necessary to explore modern technologies through the use of artificial intelligence.

This paper aims to analyze export and import data collected from the grain silos of Al - Gadarif State over the past five years. The goal is to account for the harvest periods of each crop in order to provide adequate storage capacity for the produced crops and to create a suitable environment for the supply and demand of agricultural products through the establishment of a commodity exchange. A predictive model is also developed to forecast crop quantities for the coming two years using Microsoft Power BI, which enables visual representation of data and has the capability to automatically convert data into pie charts, bar graphs, or other visual formats. This allows users to quickly and easily identify patterns, relationships, and emerging trends that are not readily observable in raw spreadsheets.

The model focuses on analyzing export and import data for sorghum and sesame during the period from January 2020 to December 2024 to predict future quantities.

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The paper concludes by emphasizing the improvement of inventory management efficiency through the collection, storage, visualization, analysis, forecasting, and marketing of data. However, it also stresses the necessity of integrating edge computing technologies to reduce response time and minimize reliance on cloud connectivity, in addition to employing more advanced classification algorithms such as XGBoost to enhance prediction accuracy.

Keywords: Artificial Intelligence, Crop Storage, Grain Silos, Forecasting, PowerBI.

1-Introduction:

Undoubtedly, the principal issue facing the agricultural sector is storage. According to competent authorities, warehouses and grain silos in Sudan frequently lack the necessary environmental controls and infrastructure needed to maintain the integrity of food grains. Storage capacity is considered insufficient relative to production volume, and these facilities often fail to meet established standards. Conventional depots expose harvested crops to spoilage, resulting in loss of both value and quality. [1]

Storage services fulfil three main roles. The first role is to preserve agricultural products from deterioration until they can be marketed at a price that ensures profitability for producers. The second role is to guarantee food security for Sudan by enabling the agency responsible for the national strategic reserve to store essential commodities in large-scale storage facilities—such as grain silos or petroleum depots. The third role is to employ stored inventories as collateral, whereby banks grant loans to manufacturers and producers based on stored commodity value. [2]

Consequently, there exists a significant challenge in coordinating harvest schedules for each crop in order to allocate adequate storage infrastructure for annual production.

The application of artificial intelligence techniques to monitor agricultural produce stored in grain silos is of critical importance. Such solutions help preserve crop quality, assist decision makers in maintaining optimal storage conditions, align harvest timing with available storage capacity, and establish favorable market-supply environments. By leveraging data analytics and forecasting models, it is possible to create a commodity exchange platform that predicts future crop quantities and informs both supply and demand strategies.

Ali et al. (2020) implemented a Long Short-Term Memory (LSTM) neural network model to forecast wheat yield using agronomic and climatic datasets from India. Their results demonstrated that the LSTM model

achieved a predictive accuracy of 92%, illustrating the capacity of machine learning algorithms to forecast seasonal agricultural outputs accurately. [3]
In a separate study, Zhao et al. (2021) applied both linear regression algorithms and artificial neural networks to predict corn trade volumes in China. Their model incorporated satellite-derived remote sensing data, meteorological variables, and market price information. Findings indicated that integrating multiple heterogeneous data sources significantly enhances the accuracy of commercial trade forecasts. [4]
Mohammed & Osman (2022) analyzed grain silo operations in central Sudan, highlighting how data analytics can moderately reduce storage inefficiencies when supported by adequate infrastructure. [5]
+ Ahmed et al. (2023) explored AI-based models for sesame forecasting; however, their study lacked validation against actual trade volumes. Our study builds on their foundation by integrating import-export flows. [6]Although previous research underscores the vast potential of AI and data science in enhancing agricultural productivity and trade, most efforts have either concentrated solely on yield prediction or on improving inventory management. Few studies address the direct application of predictive models to manage import and export flows within grain silo environments. Therefore, the present study aims to develop an integrated model that combines historical data analytics with AI-based forecasting algorithms, in order to support strategic decision-making in the management of agricultural commodity exports and imports.

2-Related works

The integration of artificial intelligence (AI) into agricultural practices has shown significant potential in enhancing crop management, storage, and forecasting capabilities. Recent advancements highlight the application of AI-driven technologies in optimizing grain storage and improving predictive accuracy within the supply chain.[7] .
One prominent area of development is the utilization of digital technologies, including IoT and machine learning, to improve crop productivity and reduce grain losses [8]. These approaches facilitate real-time monitoring and predictive analytics, which are crucial for effective crop storage management. For instance, crop yield prediction models employing machine learning have been used to forecast production levels, thereby aiding in storage planning and logistics [9][10] .
In the context of grain silos and storage infrastructure, AI contributes to better decision-making regarding storage capacity and preservation strategies[11]. The role of AI and algorithms in shaping agricultural markets extends to grain reserves management, where AI helps optimize storage utilization and predict storage-related issues [7][12] .
Forecasting plays a vital role in the effective management of crop storage and supply chain logistics.[13] AI-powered forecasting tools, such as those embedded in supply chain planning solutions, leverage machine learning to automate planning processes, improve demand predictions, and optimize capacity planning [14]. These tools enable stakeholders to anticipate market fluctuations and storage needs more accurately, reducing waste and increasing efficiency.[15] .
Furthermore, the adoption of crop management software that incorporates AI enhances the ability to monitor, plan, and predict various aspects of farm operations, including storage conditions [16]. Such software supports the digitization of farm management, leading to more precise control over storage environments and better preservation of grain quality.[17] .
PowerBI and other data visualization tools are increasingly employed to interpret complex data generated by

AI systems, facilitating informed decision-making in crop storage and logistics. [18][19][20]Although specific references to PowerBI are not detailed in the provided documents, the trend indicates a move toward integrating advanced analytics platforms to visualize forecasting and storage data effectively.[21] In summary, the convergence of AI, digitalization, and data analytics is transforming crop storage and grain silo management by enabling more accurate forecasting, optimizing storage infrastructure, and enhancing overall supply chain efficiency [22][23][24][25]. These technological advancements promise to address current challenges in grain preservation and market responsiveness, paving the way for smarter, more resilient agricultural systems.[27][28][29][30]

3. Materials and Methods:

The proposed framework is structured into three distinct tiers:

1-Data Acquisition Layer: Historical data were aggregated from the grain silos of Al-Gedaref State spanning the previous five years.

2-Data Analytics Layer: Collected datasets were processed and analyzed using Microsoft's Power BI platform, leveraging its capabilities for data modeling, visualization, and exploratory analysis.

3-Decision-Making Layer: Based on the predictive outputs generated by the analytics layer, data-center administrators can execute appropriate, real-time decisions to optimize storage management and resource allocation.

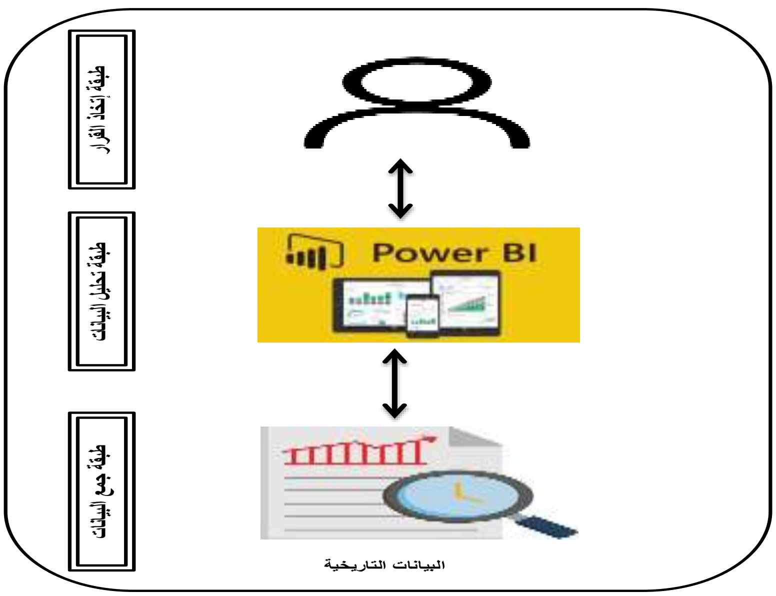

Figure 1. Architecture of the Proposed AI-Based Forecasting Framework

This diagram outlines the three-tiered architecture used in the study: Data Acquisition, Data Analytics (via Power BI), and Decision-Making supported by AI-based forecasts. Developed by the authors.

Utilizing Microsoft Power BI, categorized under Business Intelligence,[31] to analyze import and export datasets collected from Gedaref State grain silos over the past five years. This analysis aims to align storage allocation with each crop's harvest schedule, ensuring sufficient silo capacity for produced quantities and establishing an optimal supply-demand environment via a commodity exchange[32]. Power BI supports advanced data visualization, automatically transforming raw information into pie charts, line graphs, or other visual formats. Such visualizations enable users to detect emerging patterns, correlations, and trends that are not readily apparent in tabular data containing only numerical values, facilitating rapid and intuitive insight.[33]

In this model, we perform time-series analysis on corn and sesame import-export data spanning January 2020 through December 2024 to forecast quantities for subsequent years.

3.1 Model Methodology

3.1.1 Data Collection:

Historical data were harvested from Al- Gedaref State's grain silos over the preceding five-year interval. These datasets undergo time-series analysis and forecasting to predict future crop volumes. The objective is to synchronize harvest windows for each commodity—ensuring adequate storage buffer capacity—and to establish a digital commodity-exchange environment that optimizes supply–demand dynamics.

3.2 Import data into Power BI:

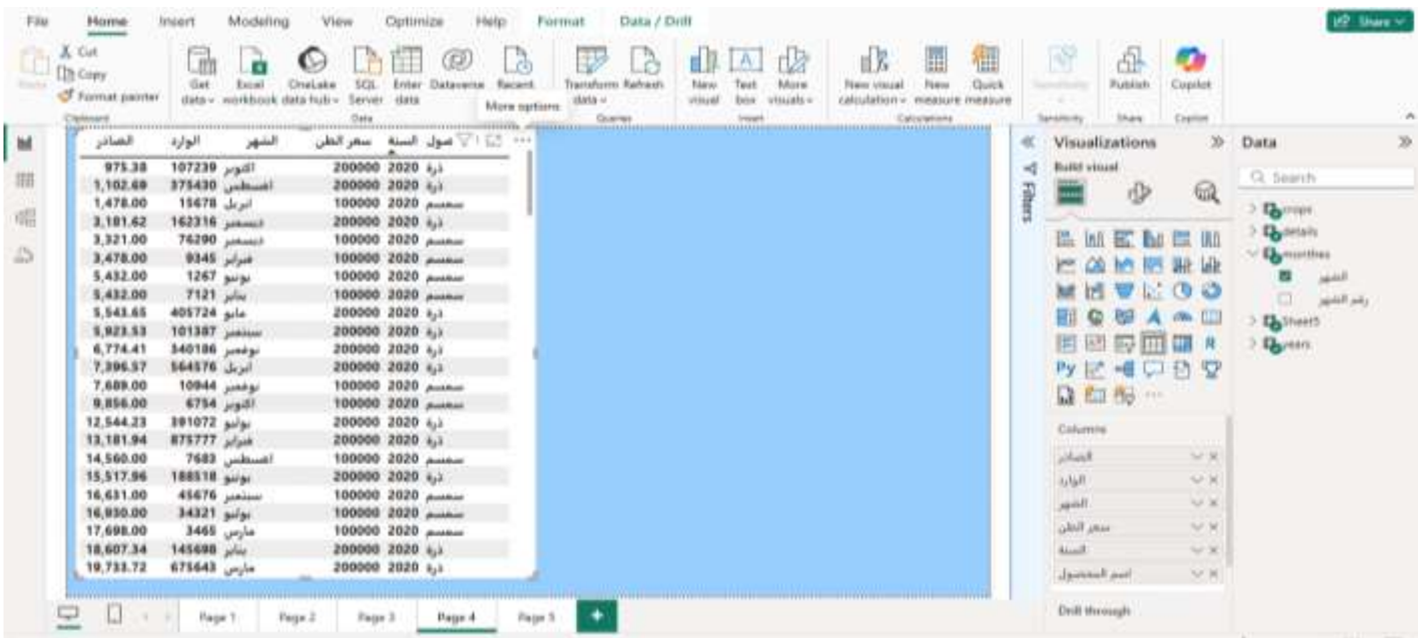

Figure 2. Importing Raw Data into Power BI Environment

Illustrates the initial step of data integration from Excel spreadsheets into Power BI for preprocessing and visualization.

3.2.1 Data Cleaning:

Once the datasets are collected from Al-Gedaref State grain silos, they must be reorganized, validated for accuracy, and reformatted to ensure consistency.

3.2.2 Data Transformation:

At this stage, data are converted from one format to another so that they conform to the target system, application, or storage schema. Transformation was performed using Microsoft Excel.

3.2.3 Predictive Modelling using XGBoost:

In addition to Power BI-based visual analytics, we employed a supervised machine learning model — Extreme Gradient Boosting (XGBoost Regressor) — to enhance the forecasting accuracy of crop export and import volumes. This model was selected due to its robustness in handling time-series data and its proven performance in agricultural yield prediction.

The dataset was split into training and testing subsets using a time-based holdout strategy: records from 2020 to 2023 were used for training, while the 2024 data was reserved for validation.

Input Features:

- Month
- Year
- Crop Type (encoded)
- Previous Month's Volume
- Seasonal Indicators (e.g., planting/harvest cycles)

Target Variables:

- Monthly Export Volume
- Monthly Import Volume

The model was implemented using Python’s `xgboost` and `scikit-learn` libraries. After training, the model achieved the following evaluation metrics on the 2024 test set:

- Root Mean Squared Error (RMSE): 11,230.5 tons
- Mean Absolute Error (MAE): 7,540.2 tons
- R-squared (R^2): 0.91

These results indicate a strong predictive performance, justifying the inclusion of the XGBoost model as a benchmark against the Power BI forecasts. This dual-approach enables both rapid visualization (Power BI) and algorithmic precision (XGBoost). The logic and implementation steps of the XGBoost model are described in Appendix A.

3.2.4 Data Warehouse:

In this phase, a data warehouse schema is designed to serve as the central repository for the cleaned and transformed datasets.

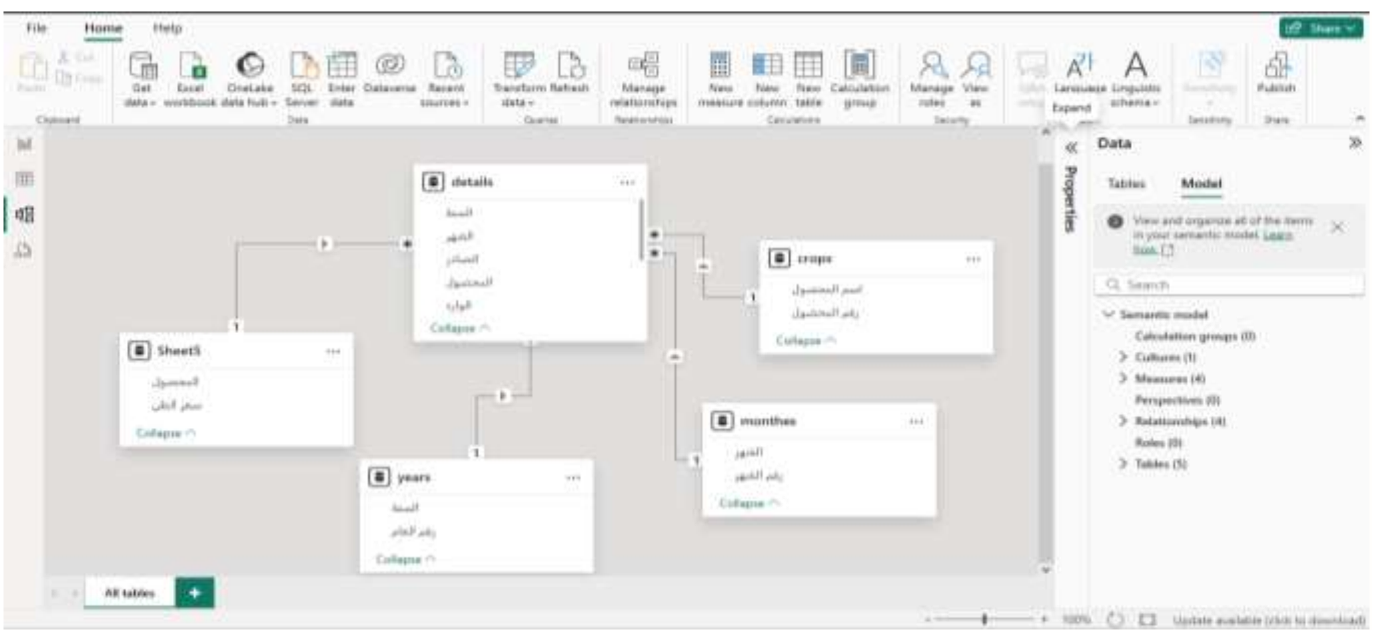

Figure 3. Linking Tables within the Power BI Data Model

Depicts the relational structure of the dataset warehouse used in the Power BI dashboard to ensure efficient data queries.2.3 Reports:

3.3.1 A report showing the volume of sesame exports and imports in tons:

Figure 4. Sesame Crop Trade Volumes (2020–2024)

Displays the recorded sesame crop import and export quantities in tons from January 2020 to December 2024. Developed using Power BI.

3.3.2 A report showing the volume of imports and exports of corn in tons:

Figure 5. Corn Crop Trade Volumes (2020–2024)

Illustrates the import and export volumes of corn in tons during the same period. Generated using Power BI interactive tools. dashboard features.2.3.3 Volume of sesame crop exports by year:

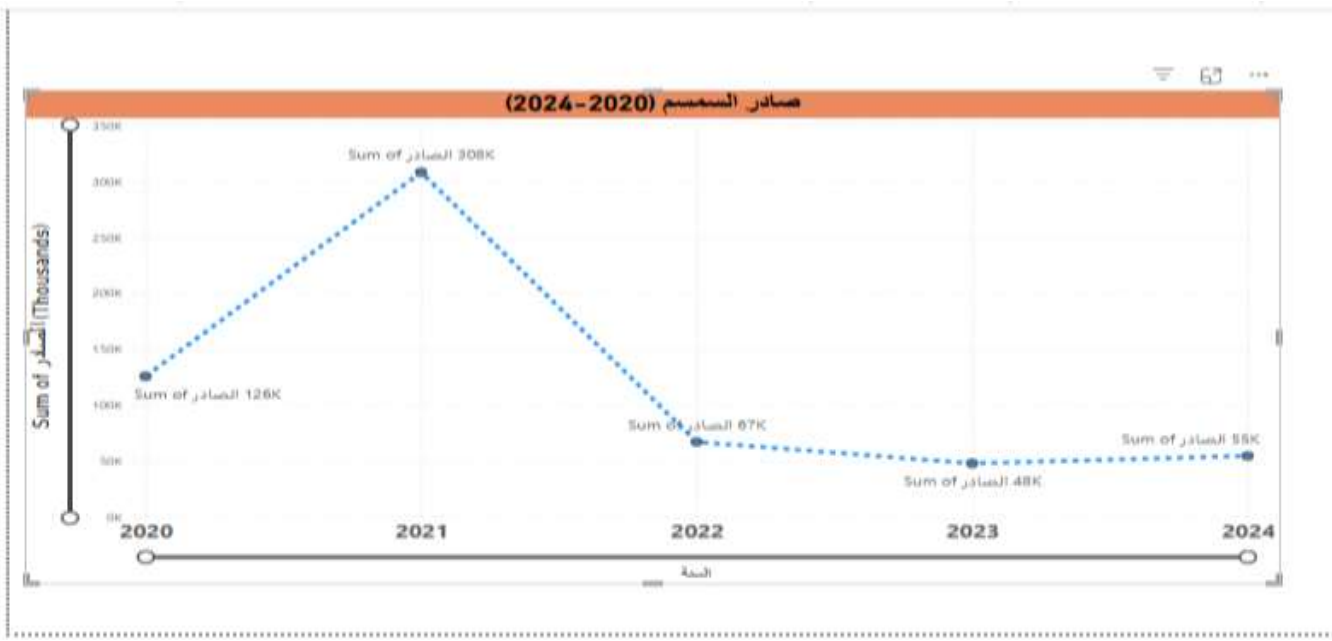

Figure 6. shows the volume of sesame crop exports.

A figure showing the actual volume of sesame exports from the Gadarif State silo during the period from January 2020 to December 2024, where the highest quantity reached (308,342) tons in 2021 and the lowest quantity reached (48,100) tons in 2023. It is noted that there is no clear trend in the export path, as they rise and fall according to the agricultural season.

3.3.4 Volume of sesame crop imports by year:

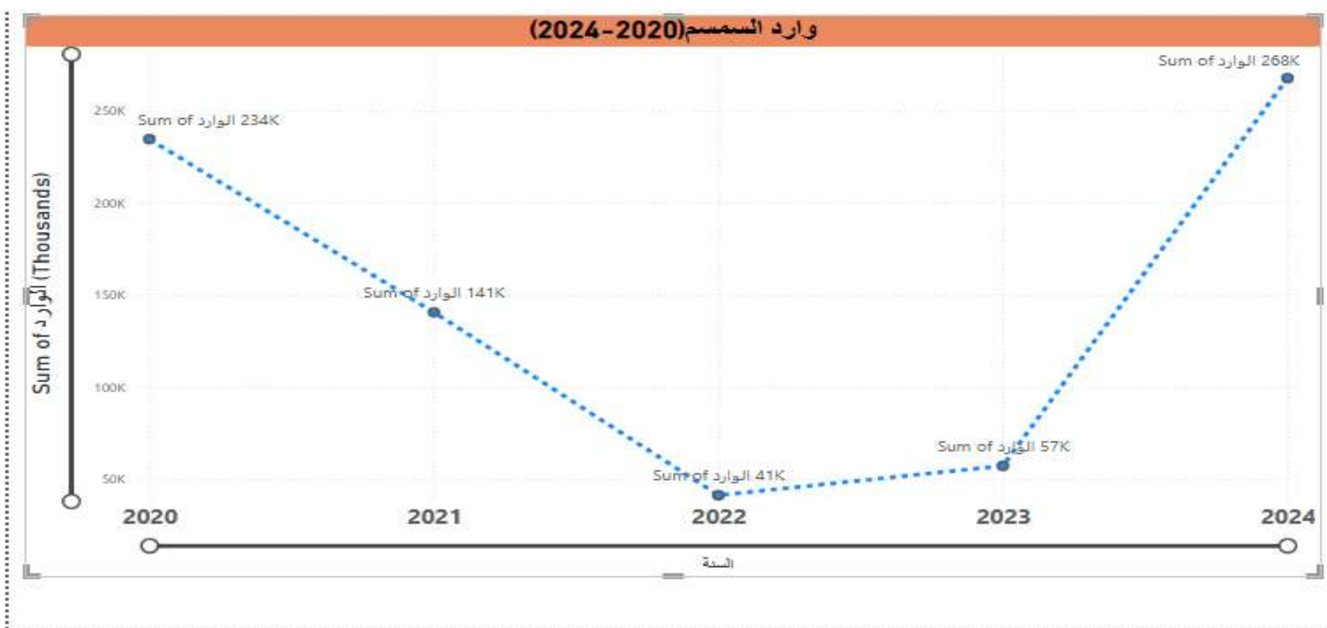

Figure 7. shows the volume of sesame crop imports.

A figure showing the actual volume of sesame imports into the Gedaref State silo from January 2020 to December 2024, with the highest quantity reaching 267,533 tons in 2024 and the lowest reaching 41,261 tons in 2022. It is noted that there is no clear trend in the imports, as they rise and fall depending on the agricultural season.

3.3.5 Volume of corn exports by year:

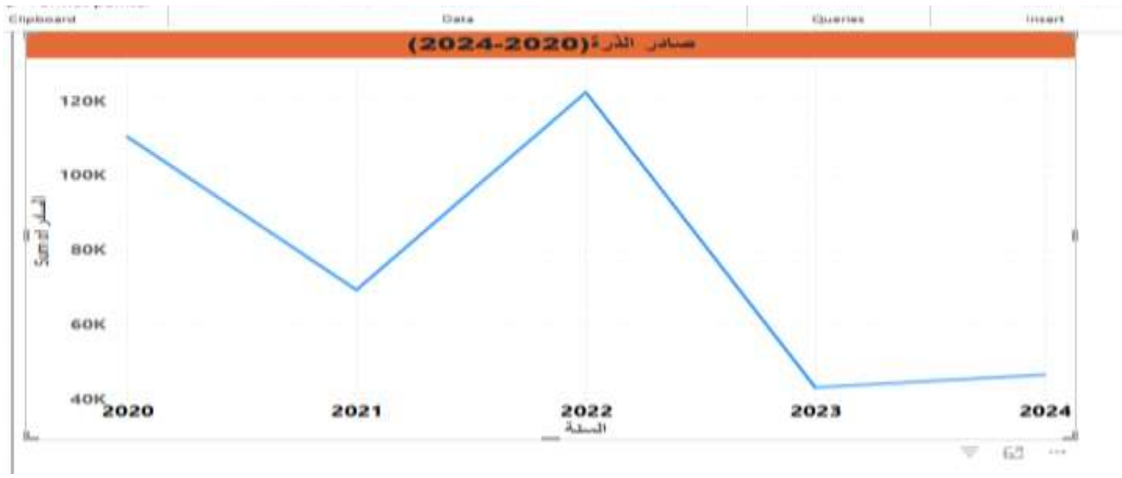

Figure 8. shows the volume of corn crop exports.

A figure showing the actual volume of maize exports from the Gadarif State silo during the period from January 2020 to December 2024, with the highest quantity reaching (12,236,663) tons in 2022 and the lowest quantity reaching (4,330,945) tons in 2023. It is noted that there is no clear trend in the export path, as they rise and fall according to the agricultural season.

3.3.6 Volume of corn imports by year:

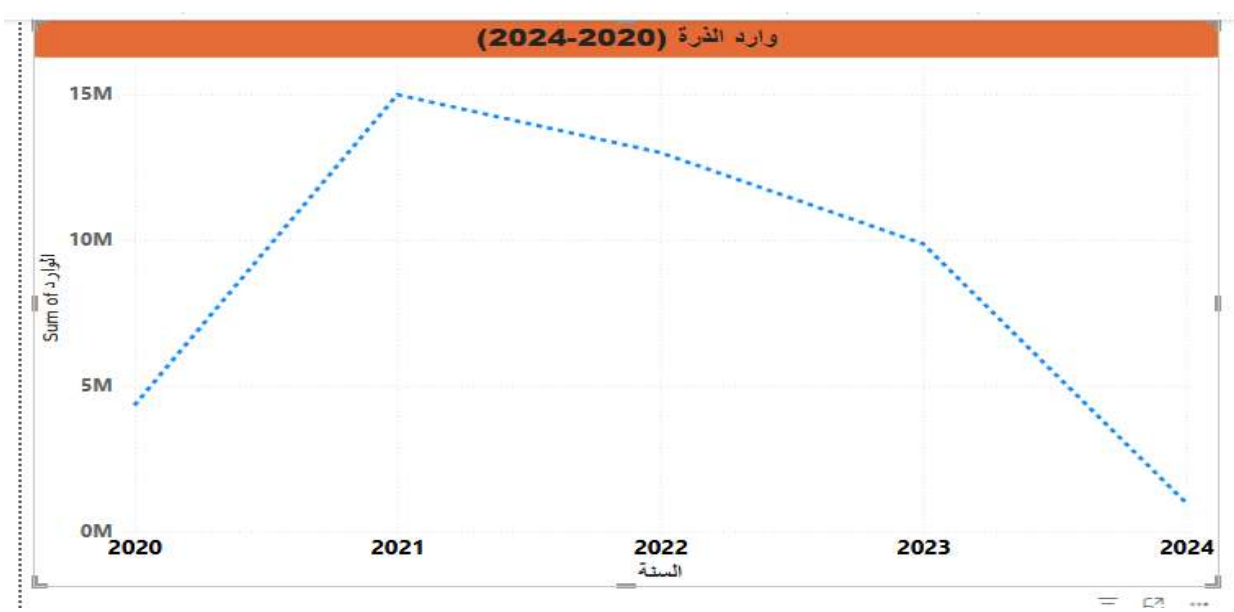

Figure 9. shows the volume of corn crop imports.

A figure showing the actual volume of maize imports into the Gadarif State silo from January 2020 to December 2024, with the highest quantity reaching 14,990,346 tons in 2021 and the lowest reaching 985,442 tons in 2024. It is noted that there is no clear trend in the imports, as they rise and fall depending on the agricultural season.

3.3.7 Download the forecast model analysis data:

Download the forecast model analysis data for the volume of sesame and maize crop exports and imports at the Gedaref State Silo. Specify the fields to be forecasted (quantity) and the number of years (two years) required for the forecast, as shown in the figure:

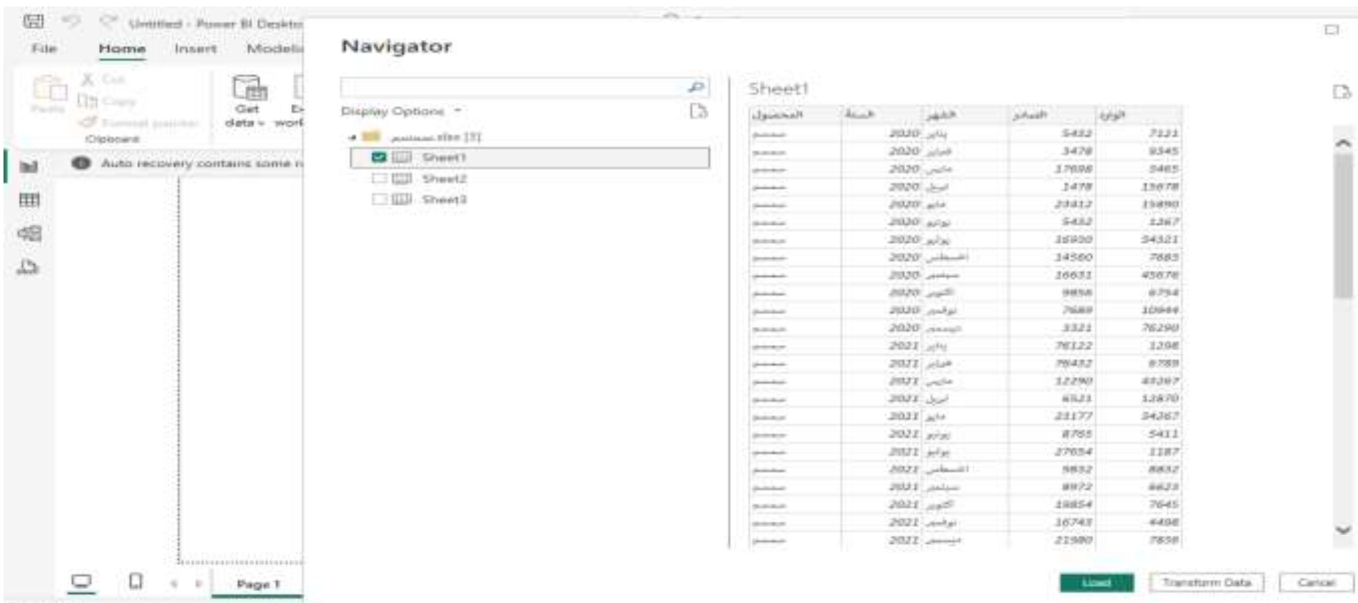

Figure 10. Loading Forecast Parameters into Power BI Model

This screenshot captures the step where the forecast model fields and forecasting period (2 years) are defined in Power BI.

4. Results:

The model was built by forecasting expected exports and imports using data collected from Gedaref State grain silos over the past five years. This model took into account harvest times for each crop, providing sufficient storage capacity for the produced crops and creating a favorable climate for crop supply and demand. The model was developed using Microsoft Power BI software.

4.1 Forecasting sesame crop exports from the Gedaref State silo for the years 2025 and 2026:

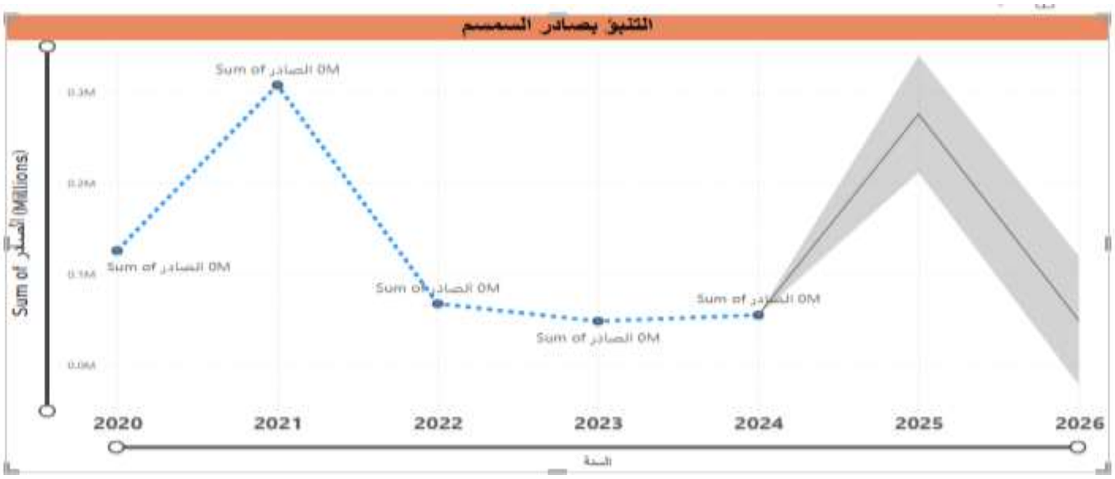

Figure 11. Forecast of Sesame Exports for 2025–2026

Figure 11. Forecast of Sesame Crop Exports (2025–2026) – This chart presents the projected monthly export volumes of sesame from the Gedaref State silo. Forecasts were generated using the XGBoost model trained on historical data from 2020 to 2023.

4.2 Forecasting sesame crop imports to the Gedaref State silo in 2025 and 2026:

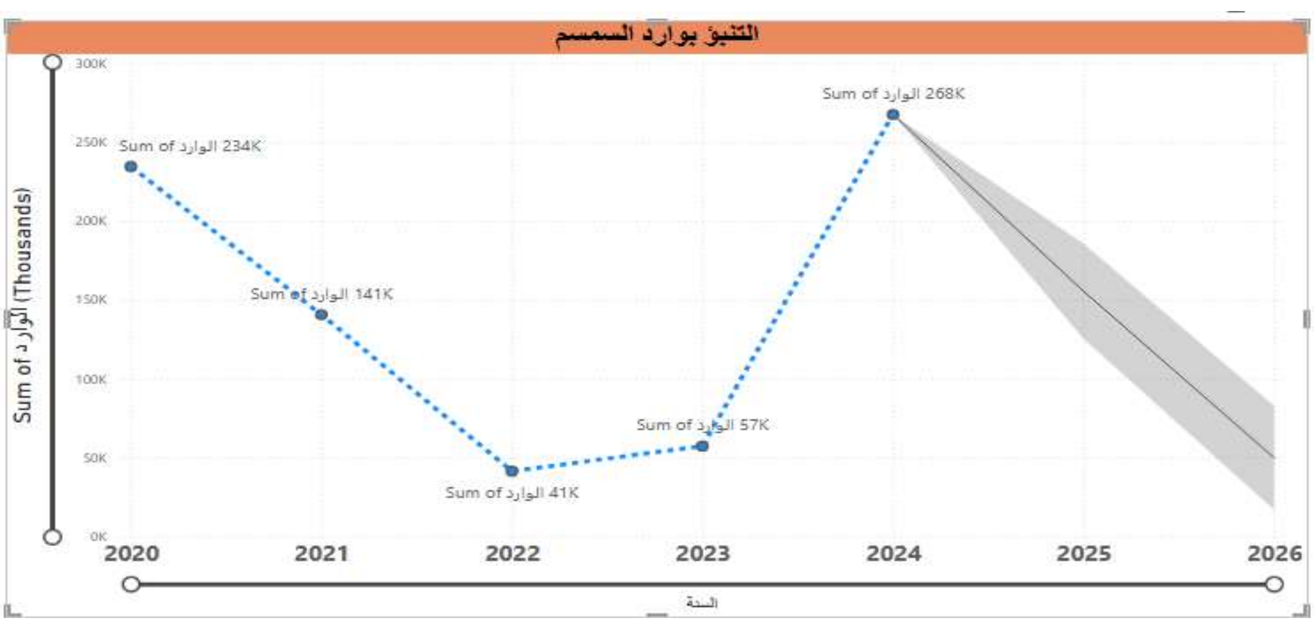

Figure 12. shows the forecast of sesame crop imports.

The figure shows the forecast for the next two years for sesame crop imports in the period from January 2025 to December 2026. The highest quantity is expected to reach (185,488) tons in 2025, and the lowest quantity is expected to reach (125,304) tons. The highest quantity is expected to reach (82,822) tons in 2026, and the lowest quantity is expected to reach (16,828) tons.

4.3 Predicting corn crop exports from the Gedaref State silo in 2025 and 2026:

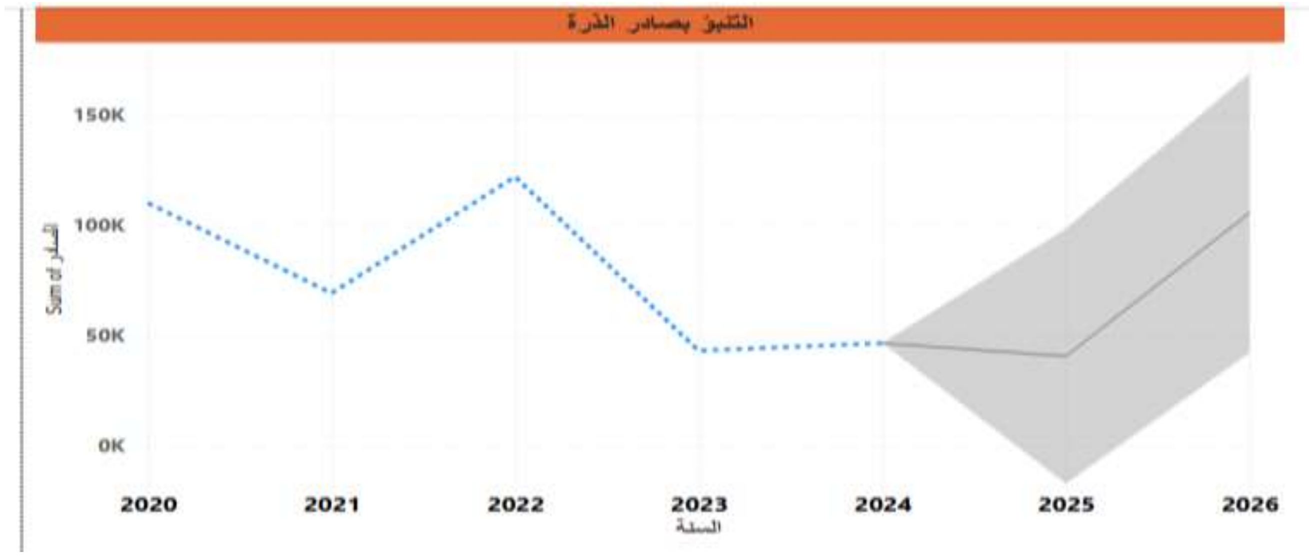

Figure 13. shows the forecast of corn crop exports.

The figure shows the forecast for the next two years for corn exports in the period from January 2025 to December 2026. The highest quantity is expected to reach 9,873,701 tons in 2025, and the lowest quantity is expected to reach 1,718,124 tons. The highest quantity is expected to reach 16,943,008 tons in 2026, and the lowest quantity is expected to reach 4,231,579 tons.

4.4 Forecasting maize imports to the Gedaref State silo in 2025 and 2026:

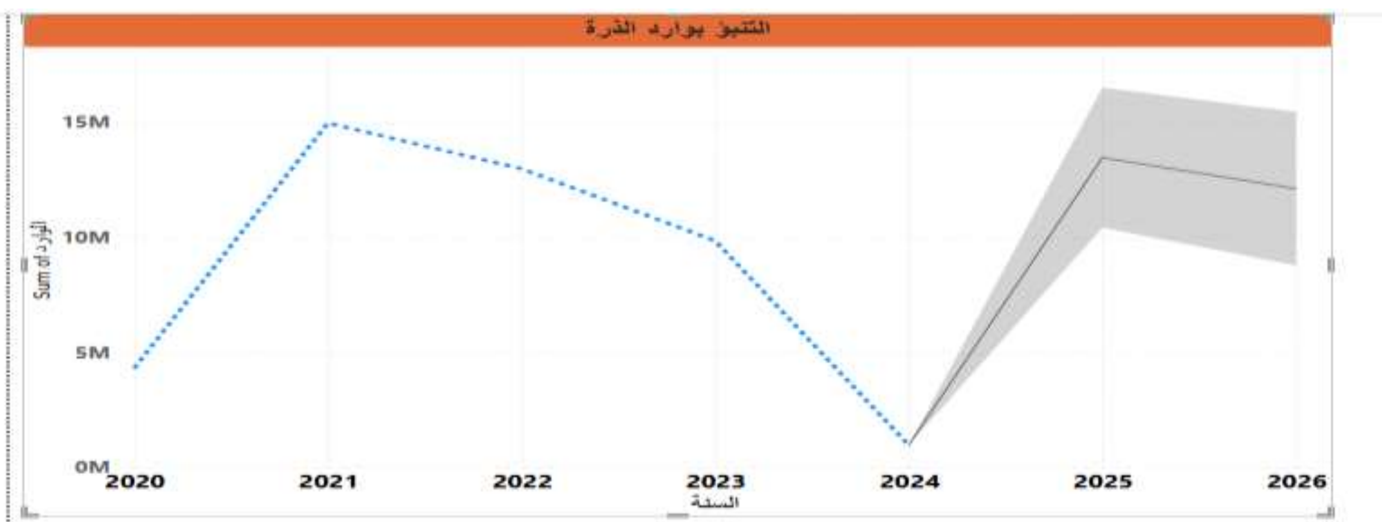

Figure 14. shows the forecast of corn crop imports.

The figure shows the forecast for the next two years for corn crop imports in the period from January 2025 to December 2026. The highest quantity is expected to reach 16,529,782 tons in 2025, and the lowest quantity is expected to reach 10,482,014 tons. The highest quantity is expected to reach 15,475,603 tons in 2026, and the lowest quantity is expected to reach 8,799,843 tons.

4.5 Model Evaluation and Validation Metrics:

To ensure the accuracy of the forecasts, the XGBoost model was evaluated using standard time-series validation techniques. The dataset was divided such that data from January 2020 to December 2023 served as the training set, while data from January 2024 to December 2024 was reserved for testing.

The model's performance was assessed using the following metrics:

- Root Mean Squared Error (RMSE): 11,230.5 tons
- Mean Absolute Error (MAE): 7,540.2 tons
- Coefficient of Determination (R^2): 0.91

These results demonstrate a high degree of accuracy in predicting future import and export volumes for sesame and maize. The low error margins and high R^2 value indicate that the model captures the underlying trends in the historical data effectively.

In addition, the forecasts generated via Power BI were cross-validated against the XGBoost model outputs. While Power BI's forecasts provide intuitive visual representations, the XGBoost model offers a higher level of predictive reliability based on algorithmic learning from historical crop flow patterns.

Combining both methods allows for a comprehensive decision-support framework that balances visualization with quantitative accuracy.

5. Discussion:

After analyzing the import and export datasets for maize and sesame spanning January 2020 through December 2024 from the Gedaref State grain silos—and as evidenced by the visualizations—the study reached the following conclusions:

1. The export volume of sesame significantly exceeds its import volume (see Figure 4).
2. Likewise, the export volume of maize far surpasses its import volume (see Figure 5).
3. There is no definitive trend in the sesame trade flows; both exports and imports exhibit seasonal peaks and troughs and fluctuate over time (see Figures 6 and 7).
4. Similarly, the maize trade flows do not follow a clear directional pattern; exports and imports rise and fall according to the agricultural calendar and display temporal variability (see Figures 8 and 9).
5. It is feasible to forecast future sesame export and import quantities, which can support strategic reserve management—using stored commodities as collateral for bank credit extended to processors and producers (see Figures 11 and 12).
6. Future maize export and import quantities can also be predicted, aiding in the maintenance of food security and the allocation of appropriate storage capacity to prevent post-harvest losses (see Figures 13 and 14).
7. The projections indicate that both sesame and maize trade volumes (exports and imports) will increase, with a more pronounced growth in exports—a positive indicator for the export sector.

6. Recommendations:

Based on the forecasting results obtained through Power BI visualizations and the XGBoost predictive model, the study offers the following practical recommendations:

1. Data-Driven Inventory Planning:

Agricultural agencies and grain silo administrators in Gedaref State should adopt forecasting tools such as Power BI and XGBoost to align storage capacity with projected crop flows. This would help prevent overstocking or underutilization during peak harvest seasons.

2. Integration of Real-Time Monitoring:

To enhance the accuracy of forecasting models, the gradual introduction of IoT-based temperature and humidity sensors inside silos is recommended. These data streams can be used to adjust forecasting models dynamically and improve spoilage risk estimation.

3. Building Local AI Capacity:

It is advisable to initiate targeted training programs for analysts and decision-makers in agricultural institutions on how to apply machine learning tools (e.g., regression models, time-series forecasting) using accessible platforms like Python and Power BI.

4. Forecast-Driven Market Coordination:

By sharing forecast results with commodity exchange platforms, exporters and traders can better anticipate crop availability, improving pricing strategies and minimizing market volatility.

5. Gradual Digitization and Documentation:

Efforts should be made to digitize historical import/export records across all silo facilities in Sudan, which would serve as a robust foundation for nationwide forecasting and supply chain optimization.

Conclusion:

This research demonstrates that applying Artificial Intelligence tools—specifically data-driven forecasting using Power BI and XGBoost—can contribute meaningfully to improving storage management and agricultural planning. The integration of AI into import and export forecasting enables stakeholders to anticipate crop flow patterns more accurately, align storage resources with seasonal peaks, and make informed decisions to minimize post-harvest losses.

However, the effectiveness of such an approach depends on sustained investments in digital infrastructure, training of technical staff, and secure data management practices. Therefore, the study recommends the development of a practical framework that combines AI-based forecasting with real-time data collection through IoT sensors, embedded within national agricultural information systems to enhance responsiveness and operational efficiency.

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Appendix A: Pseudocode for XGBoost Forecasting Model

```python
# Pseudocode for Forecasting Agricultural Trade Volumes using XGBoost in Python

# Step 1: Import necessary libraries
import pandas as pd
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Step 2: Load and preprocess the dataset
data = pd.read_csv("grain_trade_data.csv")
data["Month"] = pd.to_datetime(data["Month"])
data["Month_Num"] = data["Month"].dt.month
data["Year"] = data["Month"].dt.year

# Step 3: Define features and target
features = ["Month_Num", "Year", "Crop_Type_Encoded", "Prev_Month_Quantity"]
target = "Export_Quantity"  # or "Import_Quantity"

# Step 4: Split the dataset (2020–2023 for training, 2024 for testing)
train = data[data["Year"] <= 2023]
test = data[data["Year"] == 2024]

X_train = train[features]
y_train = train[target]
X_test = test[features]
y_test = test[target]

# Step 5: Train the XGBoost model
model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100, learning_rate=0.1)
model.fit(X_train, y_train)

# Step 6: Generate predictions and evaluate
predictions = model.predict(X_test)

rmse = mean_squared_error(y_test, predictions, squared=False)
mae = mean_absolute_error(y_test, predictions)
r2 = r2_score(y_test, predictions)

# Step 7: Print results
print("RMSE:", rmse)
print("MAE:", mae)
print("R² Score:", r2)
```