Final Project Presentation
Avocado Sales Volume Prediction

This project aimed to accurately forecast avocado sales volume using machine learning models, enabling data-driven inventory and marketing decisions. After thorough data preprocessing and exploratory analysis, we compared two main models: XGBoost optimized by Particle Swarm Optimization (PSO) and an LSTM neural network. The LSTM model outperformed XGBoost, achieving an R^2 score of 0.9209 on the test set. The final model was deployed via a FastAPI RESTful service, providing real-time sales forecasts accessible through a web interface.

by Abdelmoneim Adel

Introduction

Forecasting sales volume is critical for efficient supply chain management and customer satisfaction. This project focused on predicting avocado sales volume based on historical sales data spanning several years and geographic regions.

Data Collection and Preprocessing

Dataset Overview:

The data consists of sales records with features such as:

- date: Date of the sales record.
- average_price: Average price of avocados on that date.
- total_volume: Total volume sold.
- Codes like 4046, 4225, 4770: Representing different avocado sizes/types.
- total_bags, small_bags, large_bags, xlarge_bags: Quantities of bags sold.
- type: Avocado type (conventional or organic).
- year: Sales year.
- geography: Region of sales.

Preprocessing Steps:

- Handling missing values using interpolation.
- Encoding categorical features (type, geography) using one-hot encoding.
- Feature engineering including extracting seasonal indicators from the date.
- Normalizing numerical data to ensure scale uniformity.

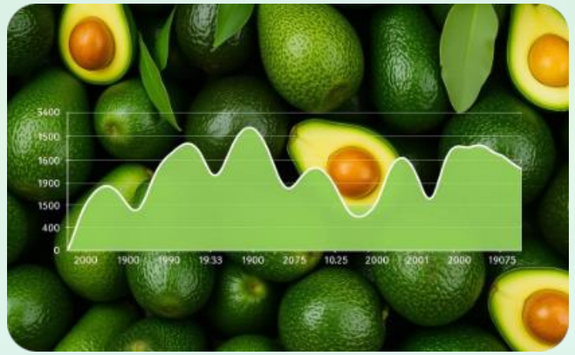
Made with GAMMA

Exploratory Data Analysis (EDA)

Key insights identified:

- Seasonal peaks in sales during holidays.
- Variations in sales volume across regions and avocado types.
- Correlations between price and sales volume trends.

Visual aids such as time series plots and correlation heatmaps were used to visualize these trends.



Seasonal Sales Patterns Patterns

Time series analysis revealed distinct seasonal patterns in avocado sales, with notable peaks during holiday periods throughout the year.

Feature Correlations

Correlation analysis between different variables helped identify key relationships, particularly between price fluctuations and sales volume.

Made with GAMMA

Model Selection and Optimization

Two main models were tested:

XGBoost

A powerful gradient boosting model, with hyperparameters optimized via Particle Swarm Optimization (PSO).

LSTM

Long Short-Term Memory neural network, effective for capturing sequential dependencies in time-series data.

PSO Optimization Details:

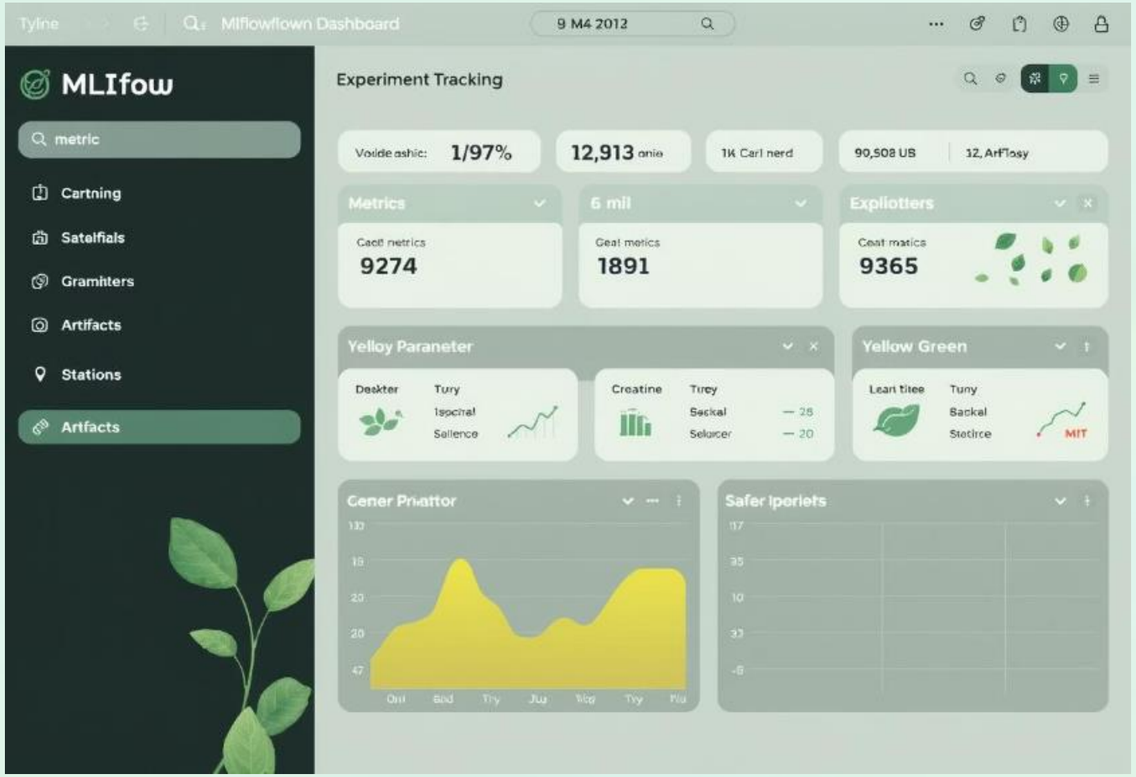
- Tuned parameters: number of estimators, max depth, learning rate, and subsample ratio.
- The optimization process iterated through multiple candidate solutions to find the best hyperparameters, which were saved and were saved and reused for efficient model training.

Made with GAMMA

Experiment Tracking with MLflow

MLflow was used for:

- Logging hyperparameters and model versions.
- Tracking evaluation metrics (MSE, MAE, R^2).
- Storing artifacts like trained models and evaluation plots. This ensured reproducibility and easy comparison of experiments.



Benefits of MLflow

Using MLflow for experiment tracking provided several advantages:

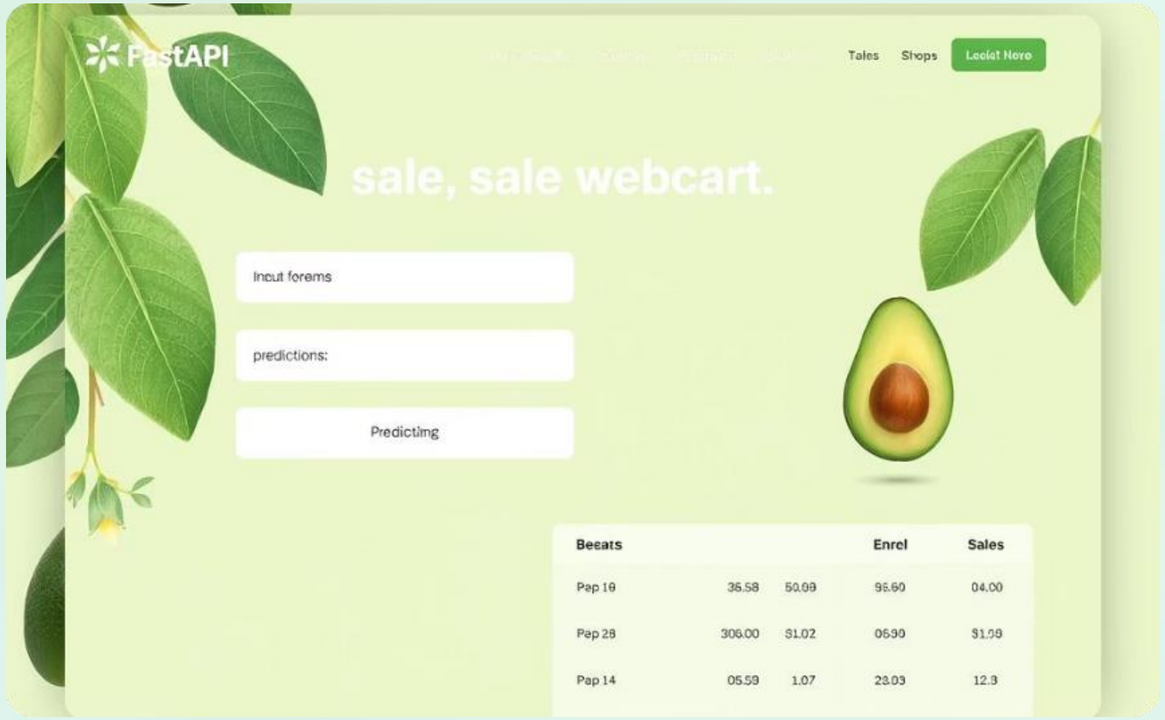
- Centralized storage of all experiment results
- Easy comparison between different model configurations
- Reproducibility of results
- Efficient model versioning

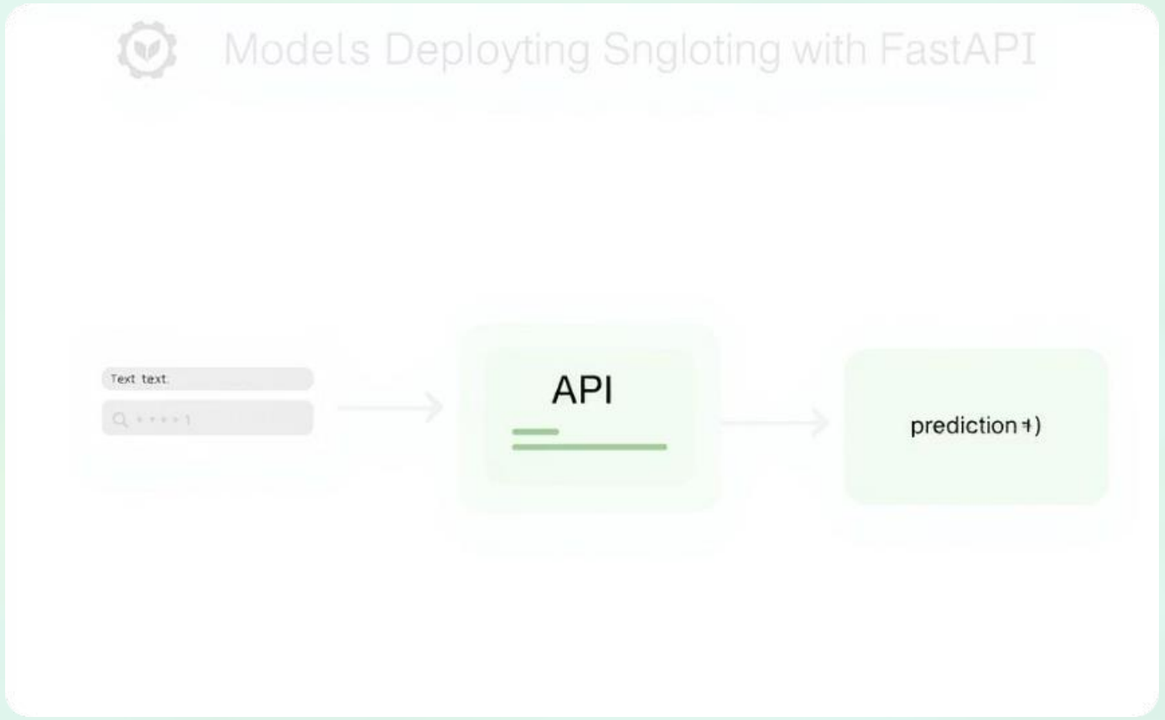
Made with GAMMA

Model Deployment with FastAPI

The best model (LSTM) was deployed as a REST API using FastAPI, hosted on Railway. Users can input 30 past sales volume values to receive forecasts on either a linear or logarithmic scale.

API link: [Avocado Sales Forecasting API]





API Interface

The FastAPI interface allows users to easily input historical data and receive sales forecasts in real-time.

Deployment Architecture

The deployment architecture ensures efficient processing of requests and delivery of predictions through a RESTful API service.

Made with GAMMA

Model Performance Comparison

The table below summarizes the evaluation metrics on the test set:

Model	MSE	MAE	R^2
XGBoost (PSO)	2.22×10^{11}	198,852.97	0.8965
LSTM	1.69×10^{11}	169,825.36	0.9209

Final evaluation of the LSTM model:

- MSE: 169,268,756,844.33
- MAE: 169,825.36
- R^2: 0.9209

The LSTM model's superior R^2 score and lower error values demonstrate its effectiveness in capturing temporal dependencies in sales data.

Made with GAMMA

Business Impact

Accurate forecasting enables:

Better inventory planning

Reduce stockouts and overstock situations through precise demand forecasting

Optimized marketing strategies strategies

Base campaigns on predicted demand fluctuations for maximum effectiveness

Increased customer satisfaction satisfaction

Ensure consistent availability of products when customers want them

Challenges and Solutions

- Data Imbalance: Different regions and types had varying data densities; addressed with careful preprocessing and feature engineering.

- Hyperparameter Optimization: PSO provided efficient tuning without exhaustive grid search.
- Deployment: Integrating the model into a RESTful API with FastAPI ensured accessibility and scalability.

Made with GAMMA

Tools and Future Work

Tools and Technologies

- Python for data processing and modeling.
- Pandas for data manipulation.
- XGBoost for gradient boosting model.
- TensorFlow/Keras for LSTM implementation.
- MLflow for experiment tracking.
- FastAPI for API deployment.
- Railway for hosting the API.

Future Work

- Incorporate external economic indicators and weather data to improve forecasting.
- Explore other deep learning architectures such as Transformers.
- Enhance the API with authentication and a user-friendly frontend interface.

Team Member

Abdelmoneim Adel Abdelmoneim

Kareem Mohamed Abdelmoneim

Eman Hassan Elqalioby

Esra’ Ehab

Thanks

Made with GAMMA

Made with GAMMA