Forecasting School Meal Production Costs: A Comparative Study of Machine Learning and Deep Learning Time-Series Models

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- **Goal**: Predict *production_cost_total* to enable efficient meal planning and waste reduction in schools.

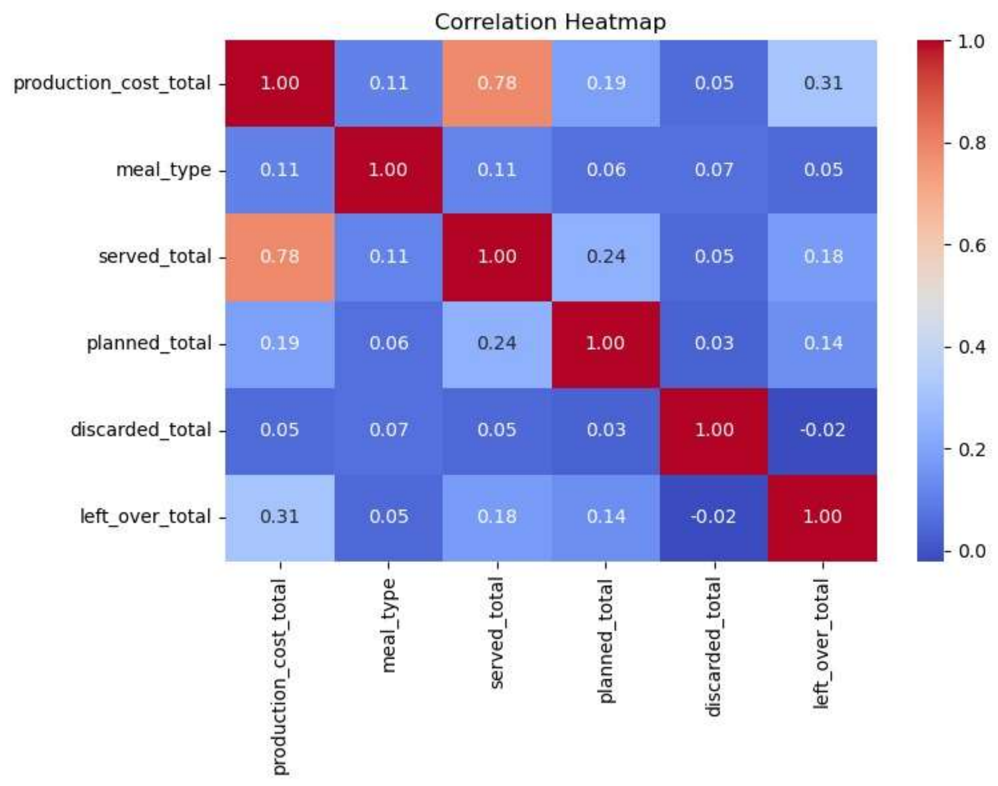
Problem Statement

- Schools struggle to predict daily meal preparation quantities.
- Inaccurate forecasts lead to food waste and increased production costs.
- Traditional methods, relying on manual estimates, are often unreliable.
- Accurate forecasting supports sustainable operations and efficient budget management.
- This project employs LSTM/GRU models to enhance cost prediction accuracy.

Data Preparation

- **Source:** 100+ FCPS HTML meal production reports
- Parsing via BeautifulSoup → structured CSVs
- Cleaned currency/percentage fields, filled missing values
- Removed outliers using IQR and 99th percentile filtering
- Final dataset: 177,492 records with daily cost and operational metrics

Exploratory Data Analysis (EDA)



- **Strong correlation:** served_total ↔ production cost (r = 0.78)
- **Moderate correlation**: leftover_total (r = 0.31)
- **Weak/no correlation**: discarded_total, meal_type
- **No multicollinearity:** VIF values < 1.3; SVD confirms good conditioning

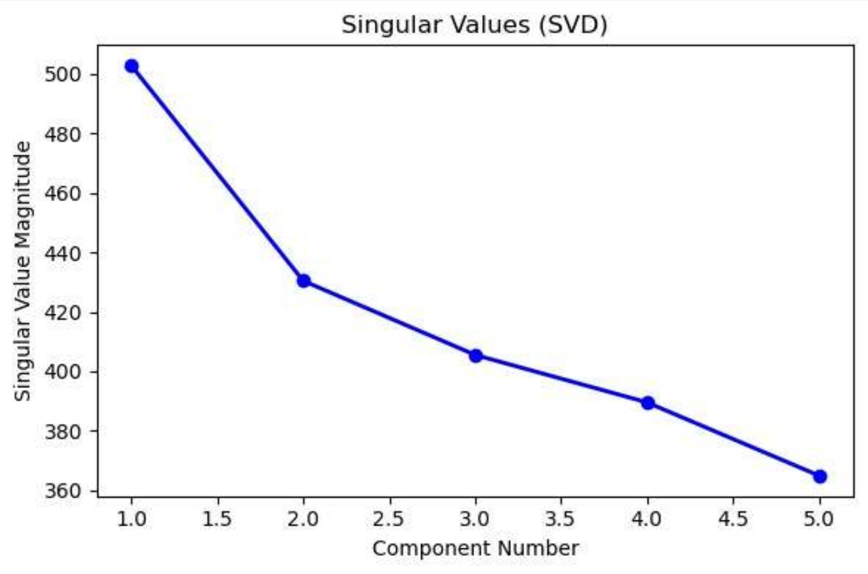
VIF and SVD Check

❖ **Variance Inflation Factor (VIF) Scores ===**

- Feature VIF
- 0 meal_type 1.265688
- 1 served total 1.284747
- 3 discarded2 planned_total 1.157264
- _total 1.028817
- 4 left_over_total 1.137335

❖ **SVD Collinearity Analysis ===**

- Singular Values:
- [502.77877511 430.43532632 405.52377947 389.56110241 364.94731802]
- No strong collinearity detected (all singular values are large).



Model Architecture

- **Goal**: Predict next-day production cost using time-series data.
- **Approaches**:
  - Univariate — Uses only past cost values
  - Multivariate — Uses cost + Served, Planned, Discarded, Leftover
- **Technique:**
  - Sliding-window (W = 3)
  - Forecast: Cost(t+1) from past 3 days
- **Models:**
  - LSTM – best for long-term patterns
  - GRU – fast, efficient alternative
  - FNN, XGBoost, Linear Regression – benchmarks
- **Train/Test Split:**
  - 60% train, 20% val, 20% test

Evaluation Metrics

Multivariate Model Performance

Model	MSE	RMSE	R_2
Linear Regression	39013.54	197.52	0.75
XGBoost	39595.32	198.99	0.74
FNN	39241.72	198.10	0.75
LSTM	**18793.44**	**137.08**	**0.86**
GRU	20186.30	142.07	0.85

- **Insight**:

GRU gave the **lowest error** (MSE & MAE), while LSTM achieved **highest accuracy** ($R^2 = 0.81$)

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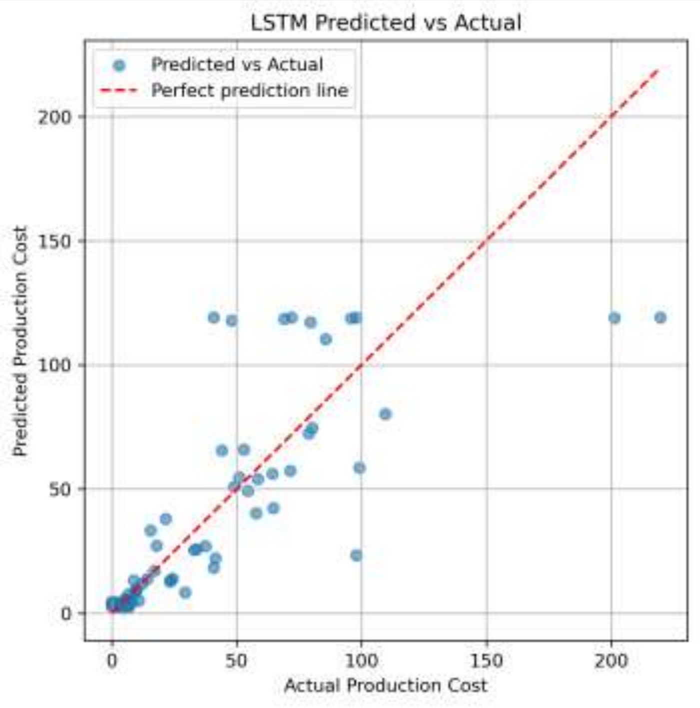
- **Insight**:

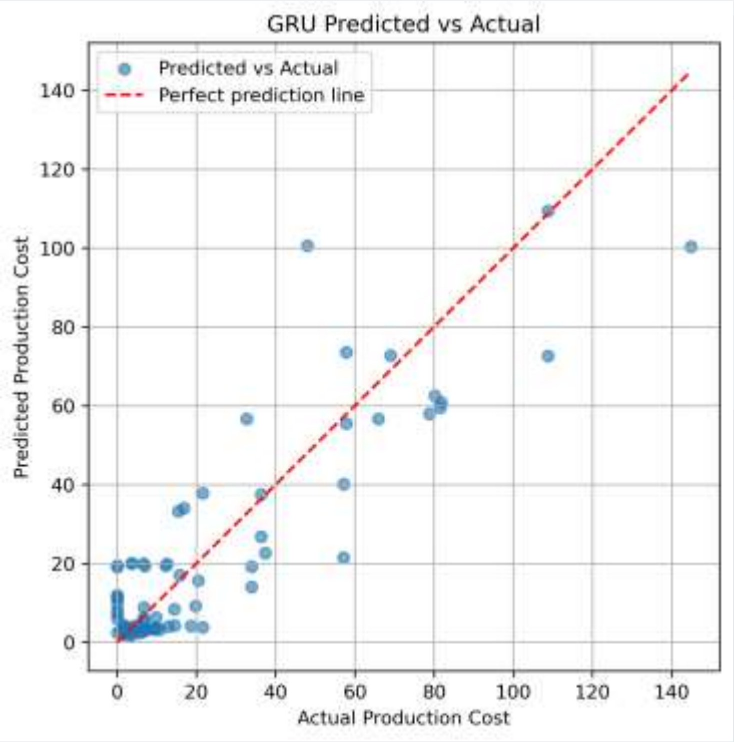
In univariate forecasting, **LSTM performed best overall**, followed closely by GRU

Multivariate Plots:

LSTM:

• Most predictions are close to the actual values
• Performs well even for higher production costs
• Slightly more scattered, but shows good overall accuracy



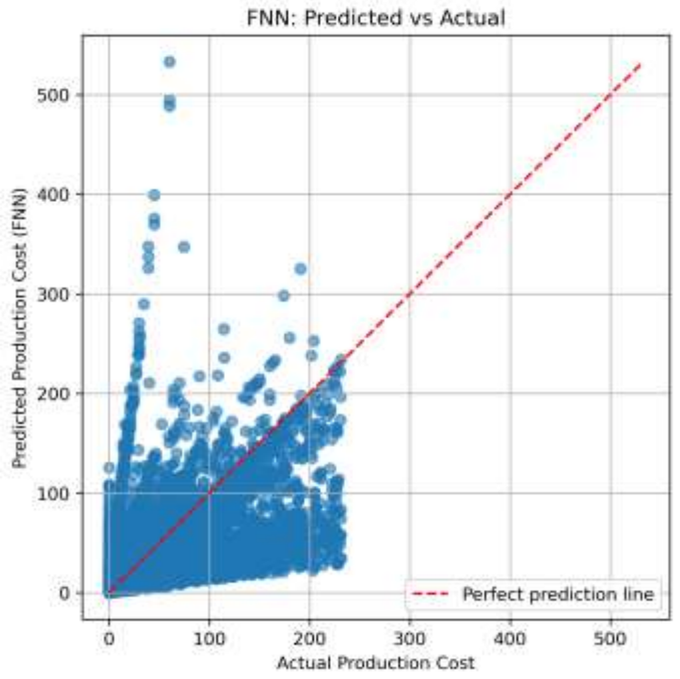


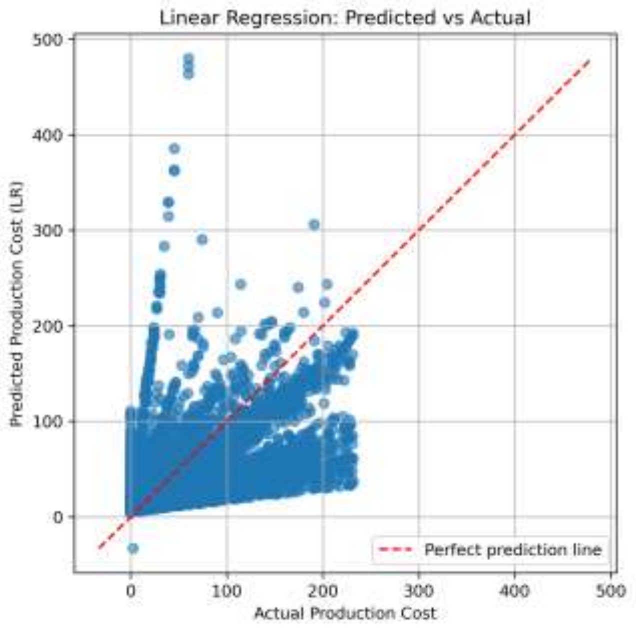
GRU:

• Predictions closely follow actual values, especially at low cost ranges
• Tighter clustering around the perfect line
• More stable for smaller-scale forecasts

FNN:

• Predictions are widely scattered around the ideal line
• Model struggles to capture time-dependent cost trends
• Less accurate compared to LSTM and GRU
• Performs decently for average costs, but poor at high-cost predictions



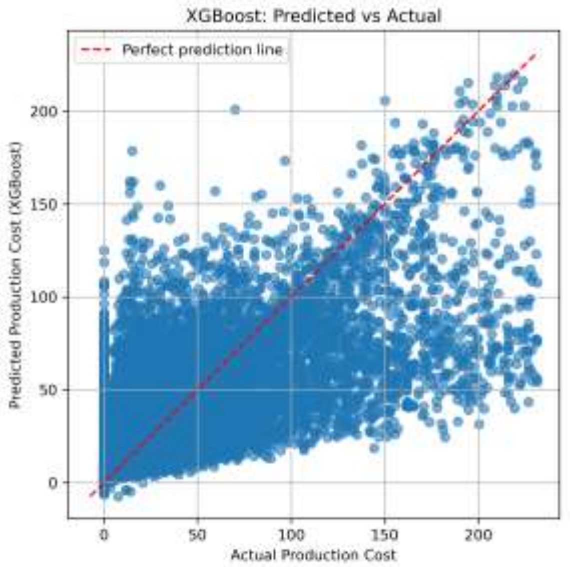


Linear Regression:

• Predictions are highly scattered, especially at higher costs
• Model fails to follow the ideal prediction line
• Can't capture nonlinear or time-based cost patterns
• Performs poorly compared to deep learning models

XGBoost:

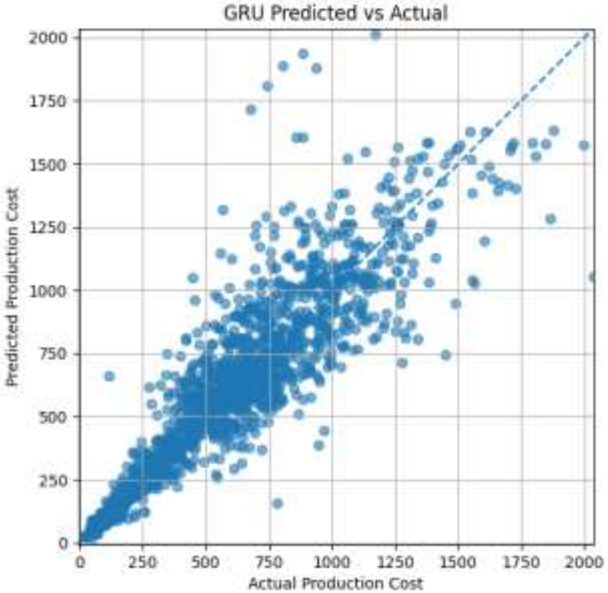
• Predictions follow the general trend but with high variance
• Performs better than Linear Regression and FNN
• Struggles with higher cost values — more scattered
• Lacks sequence-awareness, limiting forecasting precision

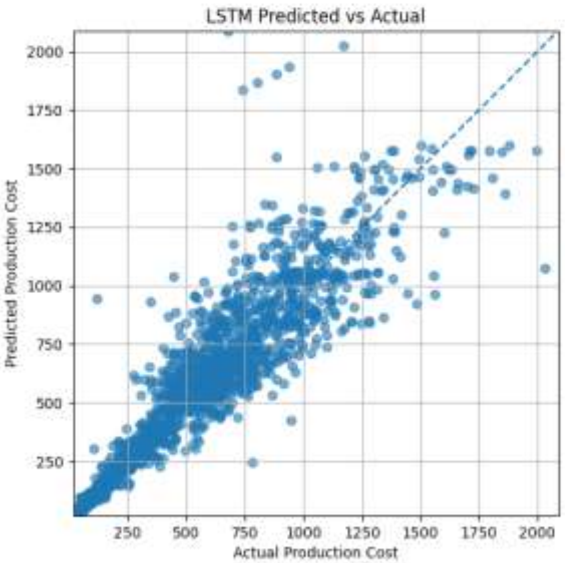


Univariate Plots:

GRU:

• Align closely with actual costs, especially at higher ranges
• Points are tightly clustered along the diagonal → strong accuracy
• Handles complex patterns across schools and meal types well
• Reliable for both small and large-scale forecasting



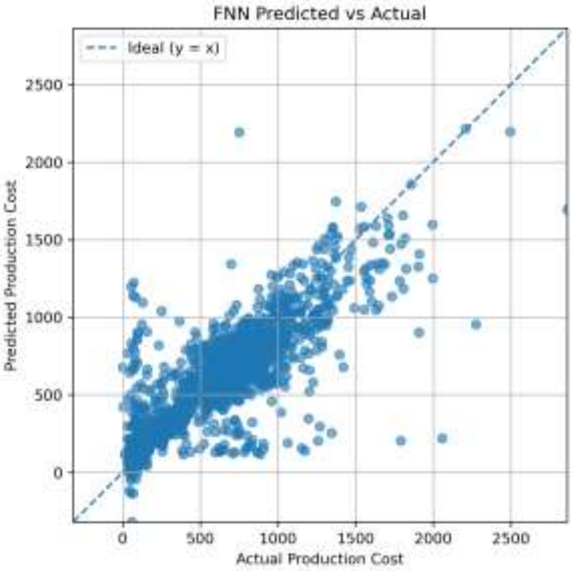


LSTM:

• Predictions closely follow actual values across the full range
• Slightly more scattered than GRU but still concentrated near the ideal line
• Captures complex temporal trends effectively
• Strong overall performance for production cost forecasting

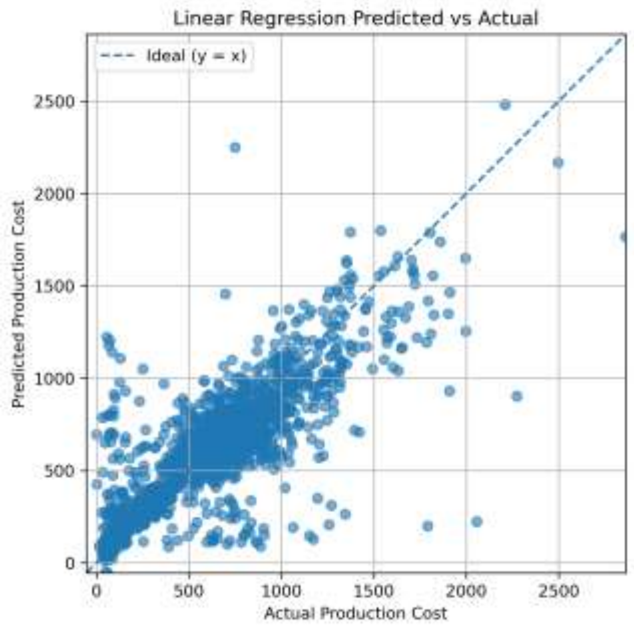
FNN:

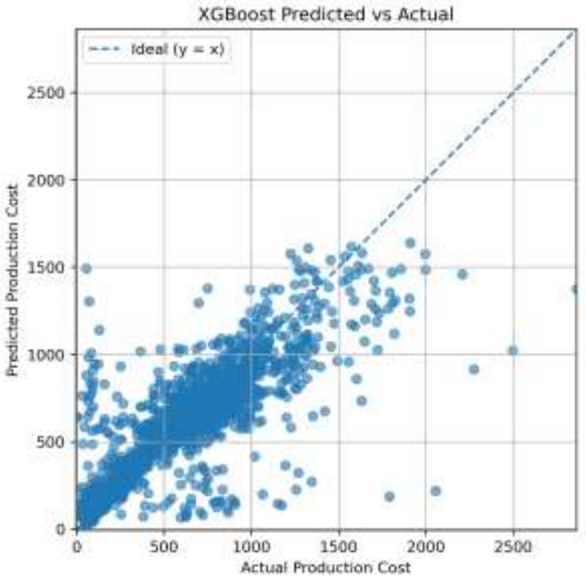
• Predictions follow the general trend but with noticeable scatter
• Performs well in mid-range values, less consistent at extremes
• Lacks memory of past values — weaker on time-series patterns
• Accuracy lower compared to LSTM/GRU, but better than Linear Regression



Linear Regression:

• Captures general trend but shows high error at both ends
• Predictions are widely spread, especially for higher costs
• Lacks ability to learn complex or nonlinear patterns
• Performs the weakest among all evaluated models



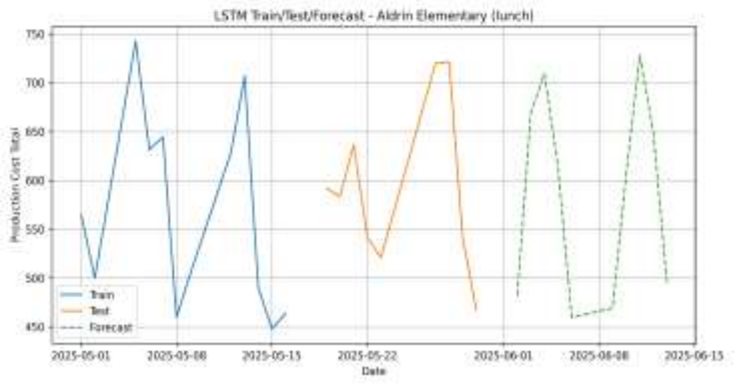


XGBoost:

• Follows the actual cost trend fairly well
• Better performance than Linear Regression and FNN
• Some spread in predictions at high cost values
• Lacks temporal learning, so accuracy dips on complex patterns

LSTM Train/Test:

• Blue: training data, Orange: test data, Green: future forecast
• Forecast continues learned patterns from past data
• Shows realistic trends in daily production cost
• Confirms LSTM captures school-specific cost behavior over time



Key Findings

- **LSTM consistently outperformed** other models with highest accuracy:
  - *R^2 = 0.81 (Multivariate)* and *R^2 = 0.86 (Univariate)*
  - Strong at capturing long-term temporal patterns

- **GRU showed lowest error (Multivariate)** and competitive accuracy:
  - Faster training than LSTM, good for near real-time needs

- **XGBoost and Linear Regression** underperformed, especially with time-series dependencies
- **Feature Insights**:
  - Served_total and Planned_total had the highest impact on cost
  - Discarded_total highlighted inefficiencies and food waste

- **Data Quality**:
  - No multicollinearity found (VIF < 2)

- **Outcome**:
  - Enables accurate **cost forecasting**, **waste reduction**, and **budget optimization** for school meal programs

Conclusion

- ✓ This project successfully developed a forecasting system for school meal production costs using advanced time-series models.
- ✓ Among all models, **LSTM and GRU** delivered the best performance, capturing temporal trends and cost patterns effectively.
- ✓ The use of **multivariate features** (served, planned, discarded meals) significantly improved prediction accuracy.
- ✓ Model results support data-driven decision making for reducing waste, improving planning, and optimizing budgets in public school meal operations.
- ✓ The interactive dashboard further enhances accessibility and practical use by stakeholders.


THANK YOU!