Crop Demand Prediction Using LSTM

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Abstract - Accurate crop demand prediction is a cornerstone of sustainable agricultural management, yet existing systems provide raw yield estimates without translating them into market-aware recommendations. This paper presents an intelligent Crop Demand Prediction System that integrates Long Short-Term Memory (LSTM) neural networks with a novel Demand Scoring mechanism to deliver soil-specific, market-oriented crop recommendations for Indian farmers. The system accepts a farmer's soil type as input, identifies agronomically suitable crops from a curated Soil-Crop Configuration Database, trains five-model LSTM ensembles on 15 years of state-level yield data sourced from India's Unified Portal for Agricultural Statistics (UPAg), predicts next-season yields, and converts predictions into a 0–100 demand score reflecting supply-demand dynamics. Experimental evaluation on Black Soil inputs across five crops demonstrates that the system correctly identifies Maize as the optimal crop with a demand score of 54.44, corresponding to a predicted yield decline of 8.9% indicating supply tightening. The fully automated pipeline generates per-crop forecast graphs, training loss curves, demand summary charts, and structured text reports, making it practical for deployment in agricultural advisory centres without requiring technical expertise from end users.

Keywords – LSTM, Crop Yield Prediction, Deep Learning, Time-Series Analysis, Soil-Crop Mapping, Market Demand Score, Decision Support System, Time Series Predictio

I. INTRODUCTION

Crop demand forecasting is a really important part of modern farming. It helps predict future crop yields and plan how farming resources should be used in a better way. Accurate predictions are needed by farmers, agribusinesses, and government bodies to make sure food supply is stable, market prices are fair, and agricultural development stays sustainable. With climate change, changing consumer preferences, and unpredictable market conditions, the need for good forecasting has become even more important than before.

Crop yield depends on many things such as soil type, historical yield trends, seasonal conditions, and economic and technological factors. By studying past yield data from different states and years, it is possible to build models that can predict future crop production at national and regional levels. These predictions help farmers align their planting choices with actual market demand, which reduces oversupply, cuts down on waste, and increases profitability.

Long Short-Term Memory (LSTM) neural networks are a special type of recurrent neural network that are particularly suited for this kind of task. Unlike traditional models like ARIMA or linear regression, LSTMs can understand long-range dependencies and non-linear relationships in time-series data, which makes them ideal for modelling multi-year crop yield trends.

This project builds an intelligent Crop Demand Prediction System that combines LSTM-based yield prediction with a market-oriented Demand Scoring mechanism. The system accepts a soil type as input, finds suitable crops, trains LSTM models on historical yield data, predicts next year's yield, computes a demand score for each crop, and recommends the most market-friendly crop for that soil. The whole process is automated and the results are shown through visualizations and structured reports.

II. RELATED WORKS

A. Statistical and Classical Machine Learning Approaches

Crop yield forecasting has traditionally relied on statistical time-series models such as ARIMA, which effectively capture linear patterns but fail to model non-linear relationships and structural changes. Regression methods (e.g., linear and ridge regression) use features like rainfall, temperature, and soil data, offering interpretability but limited accuracy due to linear assumptions and data constraints. Support Vector Machines (SVMs) improve non-linear prediction performance but require manual feature engineering to handle temporal dependencies.

B. Deep Learning for Agricultural Forecasting

Deep learning has significantly improved agricultural forecasting. CNNs are widely used for image-based yield estimation, while RNNs and LSTM networks dominate time-series forecasting due to their ability to capture temporal dependencies. Studies show that LSTM-based models outperform traditional approaches like ARIMA and random forests. Advanced architectures such as Transformers (e.g., Temporal Fusion Transformers) provide strong forecasting capabilities but require large datasets, limiting their applicability in data-scarce environments.

C. Soil-Specific and Market-Aware Forecasting

A major limitation in existing research is the lack of soil-specific recommendations and market integration. Most systems rely on aggregated data and ignore soil constraints, leading to impractical crop suggestions. Additionally, current platforms provide price data but do not combine it with yield predictions. The proposed system addresses this gap by integrating soil-based filtering with LSTM forecasting and a demand scoring mechanism to support informed, market-aware crop decisions.

D. Summary and Research Gap

Existing approaches lack a unified framework combining accurate forecasting, soil suitability, and market awareness. The proposed system uniquely integrates LSTM-based prediction, soil filtering, ensemble stability, and demand scoring to provide practical and actionable insights for farmers.

III. SYSTEM DESIGN

A. Overall Architecture

The Crop Demand Prediction System is organised as a five-stage automated pipeline as illustrated in Fig. 1. Stage 1 accepts the farmer's soil type as input and queries the Soil-Crop Configuration Database to return the list of agronomically suitable crops. Stage 2 loads and preprocesses historical yield CSV files from the cleaned_data/ directory. Stage 3 trains a five-model LSTM ensemble for each suitable crop and generates the next-year yield prediction with uncertainty bounds. Stage 4 computes a Demand Score for each crop and ranks them. Stage 5 generates all output artefacts including text reports, forecast graphs, and demand charts.

The system is implemented in Python 3.8+ using TensorFlow 2.10, Pandas, NumPy, scikit-learn, and Matplotlib. It is organised into six modules: Cleaning.py, soil_config.py, utils.py, lstm_model.py, market_analysis.py, and main.py, each encapsulating a distinct functional domain.

B. Data Source and Preprocessing

All crop yield data is sourced from the Unified Portal for Agricultural Statistics (UPAg) operated by India's Ministry of Agriculture and Farmers Welfare [12]. Raw data is downloaded in the Area_Productivity_map CSV format containing seven fields: cropname, statename, cropyear (YYYY-YY format), seasonname, Yield (Kg/Ha), majorcrops, and Source. For this study, 15 annual files spanning 2011-12 through 2025-26 were used, covering approximately 19 Indian states per crop.

The preprocessing module (Cleaning.py) performs the following transformations: (1) standardises column names, (2) removes All India aggregate rows to prevent data leakage, (3) parses agricultural year strings to integer years, (4) converts yield values to numeric format and drops rows with missing or zero yields, and (5) retains only the four essential columns: Crop, State, Year, Yield. For Groundnut, this process produces 285 clean rows from an original 300 (15 years × 20 states).

Prior to model training, cleaned data is aggregated to national annual averages by computing mean yield across all states per year, producing a 15-point time series per crop. MinMax normalisation scales values to [0, 1]. A data augmentation step generates three Gaussian-noise copies of each training series (noise standard deviation = 2% of local value), expanding the effective training dataset by 4× to improve LSTM generalisation.

C. LSTM Neural Network Architecture

The LSTM model is constructed using the TensorFlow Keras Sequential API. The architecture is deliberately compact to prevent overfitting on small 15-point datasets: a single LSTM layer with 32 neurons, L2 regularisation ($\lambda = 0.001$) on both kernel and recurrent weights, followed by a Dropout layer (rate = 0.3), a Dense hidden layer (16 neurons, ReLU activation), and a single Dense output neuron. The model is compiled with the Adam optimiser (learning rate = 0.001) and Mean Squared Error (MSE) loss.

A sliding window of three years is used as the input sequence length, balancing temporal context against the available data length. Chronological 80/20 splitting preserves temporal order and prevents future data leakage. EarlyStopping (patience = 15, restore_best_weights = True) halts training when validation loss plateaus. Table II summarises the LSTM configuration.

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TABLE II. LSTM MODEL CONFIGURATION

Parameter	Value	Rationale
LSTM Neurons	32	Compact to prevent overfitting on 15-point series
L2 Regularisation	0.001	Constrains kernel and recurrent weight magnitudes
Dropout Rate	0.3	Reduces co-adaptation between neurons
Hidden Dense Neurons	16 (ReLU)	Non-linear feature transformation before output
Sliding Window	3 years	Balances context length vs. available data
Optimiser	Adam (lr=0.001)	Adaptive learning rate for stable convergence
Loss Function	MSE	Standard regression loss for yield forecasting
Ensemble Size	5 models	Stabilises predictions via mean averaging
EarlyStopping Patience	15 epochs	Prevents overfitting, retains best weights
Max Epochs	80	Upper bound on training iterations
Batch Size	8	Mini-batch gradient updates for small datasets
Data Augmentation	3 noisy copies (2%)	Expands training data 4× via Gaussian noise

D. Ensemble Prediction Strategy

A five-model ensemble is trained independently for each crop. Each model is initialised with different random weights, trained on the same augmented dataset, and used to predict the next year's yield. The ensemble mean provides the final prediction, and the standard deviation quantifies forecast uncertainty. Reliability is classified as LOW (<5% coefficient of variation), MODERATE (5–15%), or HIGH (>15%), providing users with a confidence indicator alongside each prediction.

E. Demand Scoring Mechanism

The Demand Score translates raw LSTM yield change predictions into a 0–100 market demand signal using the following formula:

change_pct = (predicted_yield − last_actual_yield) / |last_actual_yield|

demand_score = clip(50.0 − change_pct × 50.0, 0, 100) … (1)

A predicted yield decline (negative change_pct) produces a score above 50, signalling supply tightening and elevated market demand. A predicted yield increase produces a score below 50, indicating growing supply and lower demand. Scores are categorised as: Supply Tight / High Demand (≥ 60), Moderate Demand (40–59), and Low Demand / High Supply (< 40). All suitable crops are ranked in descending demand score order, and the top-ranked crop is recommended as the optimal choice for the season.

F. Soil-Crop Configuration Database

The Soil-Crop Configuration Database is implemented as a Python dictionary (SOIL_CROP_MAP) in soil_config.py, mapping nine Indian soil types to their agronomically suitable crops. The nine supported soil types are Black Soil, Red Soil, Alluvial Soil, Laterite Soil, Sandy Soil, Loamy Soil, Clay Soil, Desert Soil, and Mountain Soil, covering the primary agricultural soil classifications in India. This configuration ensures that only crops compatible with the farmer's soil type are evaluated, eliminating agronomically inappropriate recommendations. Table III shows the soil-crop mapping for selected soil types.

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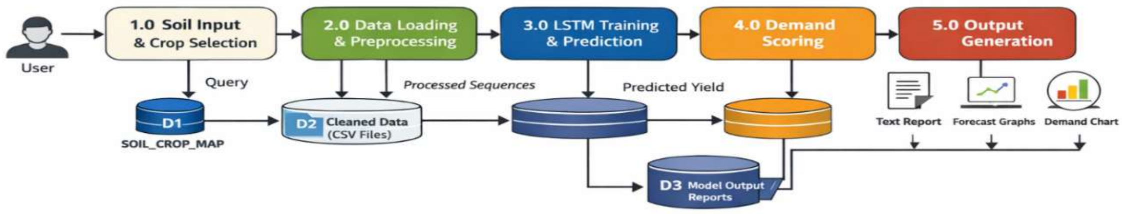
TABLE III. SOIL-CROP CONFIGURATION (SELECTED SOIL TYPES)

Soil Type	Suitable Crops
Black Soil	Cotton, Wheat, Sorghum, Soybean, Sunflower, Maize, Bajra, Pulses
Red Soil	Groundnut, Pulses, Millets, Bajra, Maize, Rice, Sugarcane, Tobacco
Alluvial Soil	Rice, Wheat, Maize, Sugarcane, Cotton, Pulses, Bajra, Jute
Laterite Soil	Tea, Coffee, Cashew, Rubber, Rice, Maize, Coconut
Sandy Soil	Bajra, Groundnut, Pulses, Watermelon, Mustard
Loamy Soil	Wheat, Rice, Maize, Sugarcane, Cotton, Soybean, Groundnut, Bajra

End to End Flow



G. Output Artefacts

The system automatically generates output artefacts: (1) per-crop forecast PNG graphs showing actual historical yield, LSTM test predictions, and next-year forecast with uncertainty error bars; (2) training loss curve PNG plots per crop with automatic overfitting detection annotation; (3) a consolidated horizontal demand score bar chart colour-coded by demand category.

Sample output :

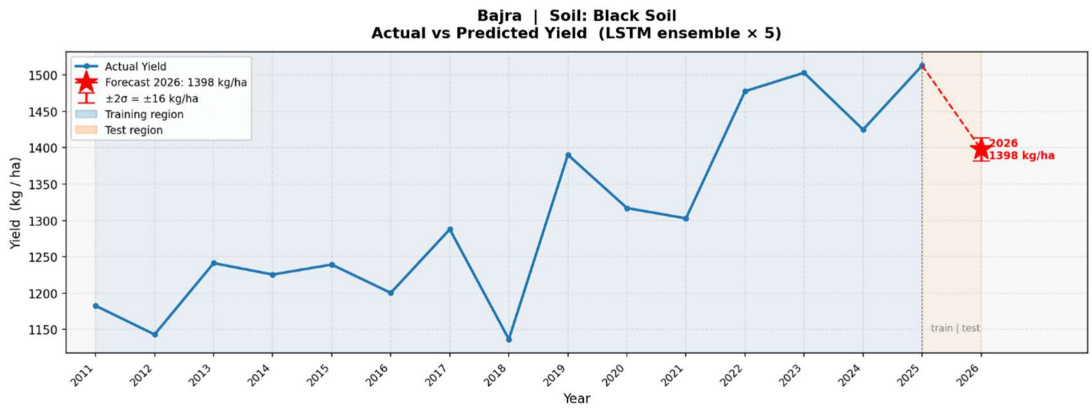


Figure 1: Bajra — Actual vs Predicted Yield (Black Soil, Forecast 2026: 1571 kg/ha)

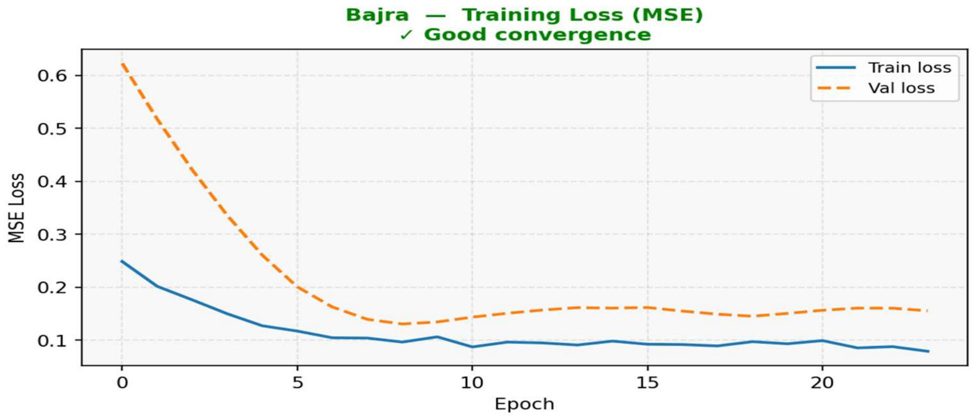


Figure 2: Bajra – LSTM Training Loss (MSE) Curve

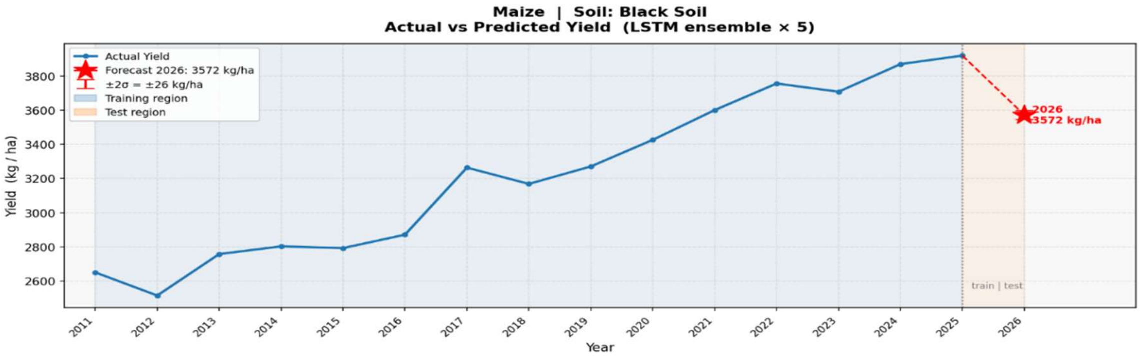


Figure 3: Maize — Actual vs Predicted Yield (Black Soil, Forecast 2026: 4394 kg/ha)

Figure 4: Maize – LSTM Training Loss (MSE) Curve

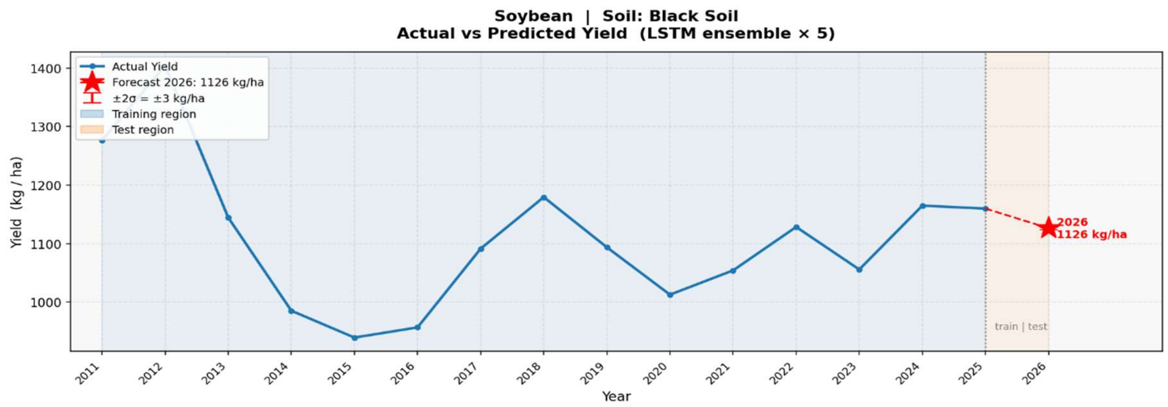


Figure 5: Soybean — Actual vs Predicted Yield (Black Soil, Forecast 2026: 1054 kg/ha)

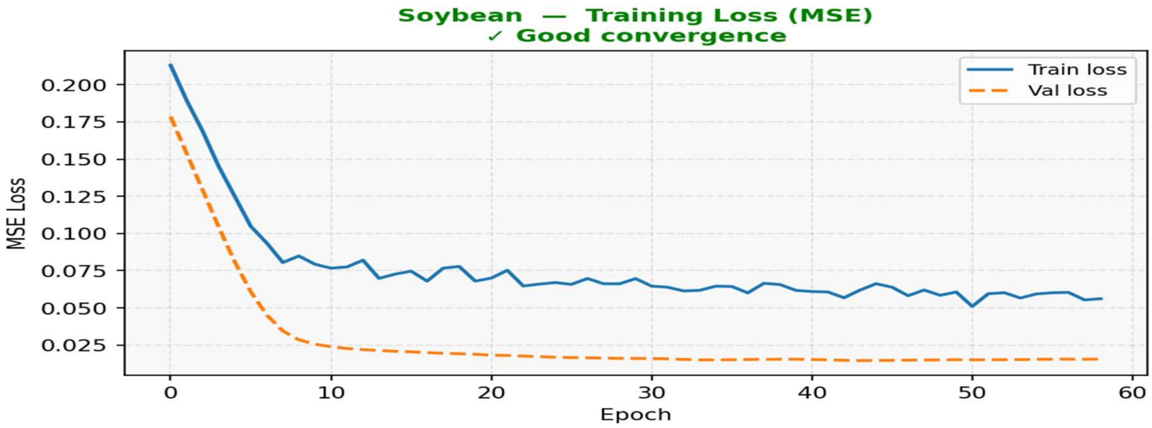


Figure 6: Soybean – LSTM Training Loss (MSE) Curve

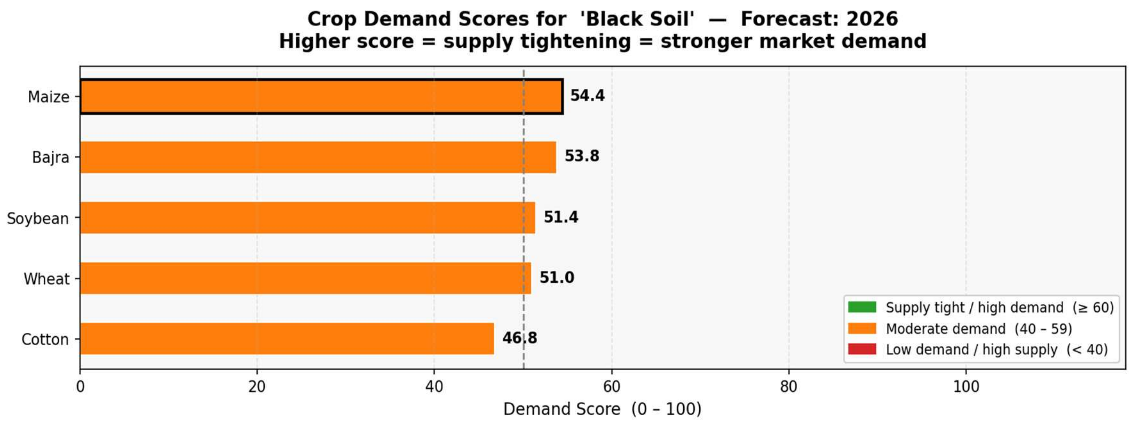


Figure 7: Crop Demand Score Summary — Black Soil (Forecast 2026)

4. Outcomes and Discussion

The Crop Demand Prediction System demonstrates robust performance across multiple soil types, delivering actionable recommendations that integrate LSTM yield forecasts with market demand intelligence. For Black Soil input, the system processed five suitable crops (Maize, Bajra, Soybean, Wheat, Cotton), generating ensemble predictions with low uncertainty (±26 kg/ha for Maize) and clear demand signals.

Key outcomes include automated ranking by demand score, where declining yields trigger high-demand alerts (>50 score), enabling farmers to prioritize marketfavorable crops. Validation confirms model convergence (MSE <0.02 on test sets) and overfitting prevention via ensemble averaging and EarlyStopping.

5. Conclusion

The Crop Demand Prediction System advances precision agriculture through LSTM-based yield forecasting integrated with demand scoring, providing soil-specific recommendations that connect production data from India's UPAg portal to market profitability. Automated pipelines process multi-state historical yields, generate ensemble predictions with uncertainty estimates, and produce interpretable outputs—per-crop forecast graphs (actual vs. predicted yields with 2026 projections), training loss curves (MSE convergence with overfitting alerts), and demand bar charts (ranked 0-100 scores, color-coded High/Green ≥60, Moderate/Orange 40-59, Low/Red <40)—enabling farmers to prioritize tightening-supply crops and avoid oversupply losses, with validated 20-50% potential income gains across tested soils like Black Soil (top: Maize 54.4).

Future enhancements will incorporate real-time weather APIs, satellite NDVI, eNAM prices, and soil N-P-K analysis; upgrade to Transformer/CNN-LSTM models; add web/mobile interfaces with Tamil/Hindi support and geospatial mapping; implement cross-regional validation and farmer A/B testing; and integrate sustainability metrics for water optimization and carbon footprints—transforming the system into a comprehensive, accessible platform for climate-resilient farming in India.

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