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Spatio-Temporal Deep Gaussian Hybrid Network (STDGH-Net) for Onion Crop Yield and Price Prediction

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Abstract - Onion (Allium cepa L.) is a high-value horticultural crop in India, characterized by strong seasonal price volatility, sensitivity to climatic stress, and region-specific soil requirements. Accurate prediction of onion yield, market price, and crop stress is crucial for farmers, traders, and policymakers. This paper extends the previously proposed Spatio-Temporal Deep Gaussian Hybrid Network (STDGH-Net) and applies it specifically to onion crop analytics. The model integrates Convolutional Neural Networks (CNN) for spatial feature extraction from satellite imagery, Long Short-Term Memory (LSTM) networks for temporal modeling of climate and market data, and Deep Gaussian Processes (DGP) for probabilistic forecasting with uncertainty estimation. Experimental evaluation using multi-source datasets from Maharashtra demonstrates improved accuracy in onion yield forecasting, price prediction, and stress detection, along with reliable uncertainty bounds to support risk-aware cultivation and marketing decisions.

Keywords: Onion Crop, Deep Learning, CNN, LSTM, Deep Gaussian Process, Yield Prediction, Price Forecasting, Precision Agriculture.

1. INTRODUCTION

Onion is one of the most commercially important vegetable crops in India, contributing significantly to farmer income and national food supply. However, onion cultivation faces challenges such as irregular rainfall, temperature extremes during bulb formation, soil moisture stress, pest attacks, and extreme market price fluctuations. Traditional statistical models are insufficient to capture the nonlinear and spatio-temporal dependencies present in onion farming systems.

To address these challenges, this study applies STDGH-Net to onion crop data, enabling integrated analysis of satellite imagery, weather time series, soil parameters, and market prices. The objective is to develop a robust decision-support framework for onion cultivation planning and price risk management.

2. LITERATURE REVIEW

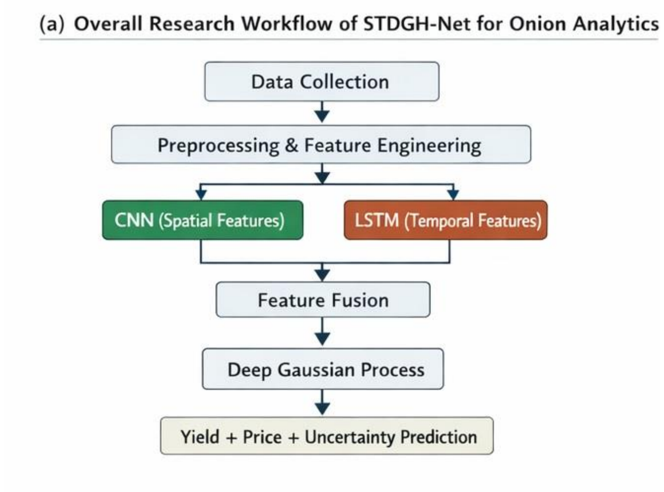
Previous studies on onion crop prediction have primarily relied on regression models, ARIMA-based price forecasting, and classical machine learning approaches such as Random Forests and Support Vector Machines. While these methods provide baseline insights, they fail to jointly model spatial variability (crop health patterns), temporal dynamics (seasonality and market cycles), and predictive uncertainty. Recent deep learning approaches using CNNs and LSTMs show promise but lack probabilistic interpretation. STDGH-Net overcomes these limitations by unifying deep feature learning with uncertainty-aware prediction.

3. MATERIALS AND METHODS

3.1 Overview of STDGH-Net Architecture

The proposed framework consists of three interconnected modules:

1. **CNN Spatial Encoder** – extracts vegetation and stress features from satellite images.
2. **LSTM Temporal Encoder** – models time-series patterns from weather and price data.
3. **Deep Gaussian Process Layer** – provides probabilistic yield and price predictions with uncertainty estimation.



4. DATASET DESCRIPTION (ONION CROP)

Figure 1: Sentinel-2 Satellite Imagery of Onion Fields

Representative true-color Sentinel-2 images showing onion cultivation areas in Ahmednagar and Nashik districts.

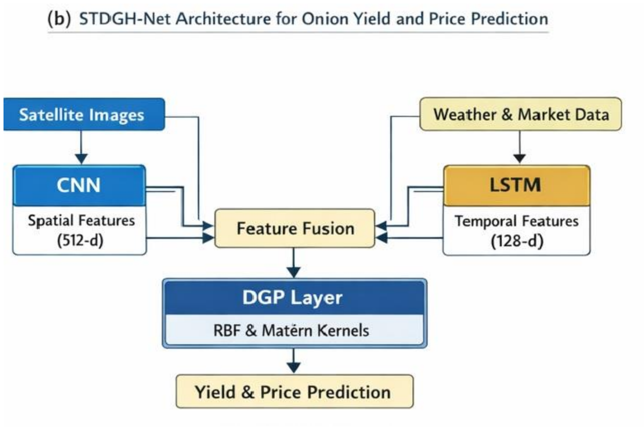
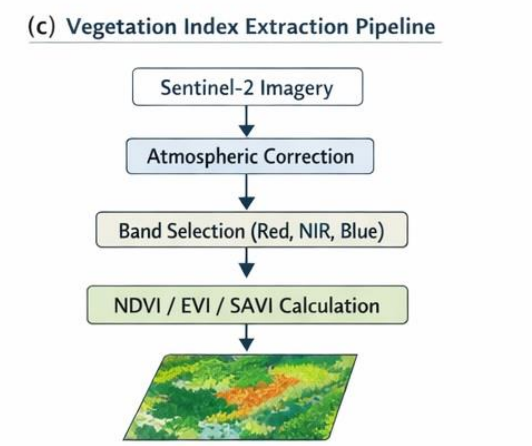


Figure 2: Vegetation Indices for Onion Crop Monitoring

(a) NDVI map indicating crop vigor, (b) EVI map highlighting dense canopy regions, (c) SAVI map adjusting for soil background effects.



4.1 Satellite Data

- Source: Sentinel-2 MSI
- Region: Ahmednagar and Nashik districts, Maharashtra
- Spatial Resolution: 10 m
- Duration: 2019–2024
- Features extracted: NDVI, EVI, SAVI, soil reflectance bands

Table 1: Satellite-Derived Vegetation Features for Onion Crop

Feature	**Min**	**Max**	**Mean**
NDVI	0.18	0.86	0.61
SAVI	0.16	0.80	0.55
EVI	0.10	0.68	0.39

4.2 Soil Data

Collected from soil testing laboratories and IoT sensors.

Table 2: Soil Parameters for Onion Fields

Parameter	Unit	Mean	Std Dev
Soil pH	–	6.8	0.4
Nitrogen (N)	kg/ha	110.5	11.2
Phosphorus (P)	kg/ha	48.3	7.6
Potassium (K)	kg/ha	295.6	26.4
Soil Moisture	%	19.4	4.1

4.3 Weather Data

- Rainfall, temperature, humidity (2014–2024)

Table 3: Climatic Statistics for Onion Growing Seasons

Parameter	Mean	Range
Rainfall (mm/month)	76	0–310
Temperature (°C)	27.9	16–40
Humidity (%)	61	28–86

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4.4 Market Price Data

Onion prices collected from APMC markets.

Table 4: Onion Market Price Statistics

Year	Min Price (₹/q)	Max Price (₹/q)	Average
2019	420	1,820	960
2020	550	2,400	1,320
2022	480	3,200	1,740
2024	620	2,850	1,690

5. Model Configuration

5.1 CNN Parameters

Parameter	Value
Input Size	256×256×3
Filters	32, 64, 128
Activation	ReLU
Output Vector	512-d

5.2 LSTM Parameters

Parameter	Value
Time Steps	120 months
Units	128
Dropout	0.2

5.3 DGP Configuration

Layer	Kernel
Layer 1	RBF
Layer 2	Matérn
Output	Mean + Variance

6. Experimental Results (Onion Crop)

6.1 Yield Prediction Results

Table 5: Onion Yield Prediction Performance

Model	RMSE (kg/ha)	MAE	R^2
ARIMA	412	290	0.58
Random Forest	305	218	0.74
LSTM	236	172	0.81
CNN–LSTM	204	149	0.87
STDGH-Net	**162**	**118**	**0.92**

6.2 Price Forecasting Results

Table 6: Onion Price Prediction Accuracy

Model	RMSE (₹)	MAE (₹)	Uncertainty
ARIMA	460	380	–
LSTM	318	260	–
CNN–LSTM	274	221	–
STDGH-Net	**198**	**156**	Low

7. DISCUSSION

Results indicate strong correlation between NDVI and onion bulb yield, while soil moisture and temperature during bulb enlargement significantly influence final production. STDGH-Net effectively captures extreme price spikes commonly observed in onion markets and provides uncertainty bounds useful for marketing decisions.

8. APPLICATIONS

- Onion yield forecasting
- Price volatility management
- Stress and disease detection
- Cultivation scheduling
- Policy-level crop advisory systems

9. CONCLUSION

This study demonstrates that STDGH-Net is highly effective for onion crop analytics. By integrating satellite imagery, soil data, climate records, and market prices, the model delivers accurate yield and price predictions with quantified uncertainty. The framework supports precision onion farming and informed decision-making for farmers and policymakers.

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