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Fusing Deep Learning and Control Theory for Optimized Sugar Beet Yield Prediction

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ABSTRACT

Accurate yield prediction is a vital field of research in precision agriculture, enabling optimal resource allocation and enhanced food security under growing climatic uncertainty. Traditional models struggle to capture complex, non-linear interactions between environmental drivers and crop growth. To address this, we present our approach, a multi-stage method for sugar beet yield prediction and management that integrates deep learning with control-theoretic techniques and mathematical language modelling. Our pipeline begins with the processing of multivariate farm data, such as satellite imagery and field sensor measurements, with a convolutional neural network (CNN) empowered by spatial and temporal attention mechanisms to learn discriminative features. A system identification layer translates the learned representations into a state-space model that characterizes the latent crop growth dynamics. The sequential time frames are then mapped by a bidirectional LSTM (Bi-LSTM) network to provide prediction. The standout introduction is a mixture-of-experts (MoE) module that provides actionable recommendations. The module forwards specific agronomic queries to targeted agents based on Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG). Every agent is an expert in one of the sub-domains, like irrigation, fertilization, or pest management. This proposed integrated framework bridges the gap that currently exists between high-level AI and actual agronomy, giving stakeholders correct, data-driven plans to maximize resource use, improve climate resilience, and facilitate sustainable production.

Keywords: Yield Prediction, Deep Learning, System Identification, Mixture-of-Experts, Decision Support System, Sugar Beet

INTRODUCTION

Sugar beet (*Beta vulgaris L.*) is a cornerstone of European agriculture. The European Union is the world's leading producer of beet sugar, accounting for approximately 50% of the global total, with Germany being one of the most significant producers (European Commission, 2024). Current approaches to yield prediction are ill-equipped to navigate this complex landscape. Traditional process-based Crop Simulation Models (CSMs), while offering mechanistic interpretability, demand extensive site-specific calibration and struggle to integrate diverse, real-time data streams (Anar et al., 2019; van Ittersum and Rabbinge, 1997). Conversely, modern Machine Learning (ML) models excel at fusing heterogeneous data to achieve high predictive accuracy but typically operate as opaque "black boxes," which provides little insight into the drivers of their predictions to the farmers (Khaki, Wang, and Archontoulis, 2020). This work introduces a hybrid framework designed to resolve this trade-off. By synergistically fusing deep learning with control theory, the proposed system aims to deliver high-accuracy yield predictions while generating a dynamically interpretable model of crop growth. Crucially, it translates these complex outputs into actionable, evidence-based agronomic recommendations via a pioneering Mixture-of-Experts (MoE) module.

MATERIALS AND METHODS

Data Ingestion and Spatio-Temporal Feature Extraction

The pipeline ingests multivariate time-series data essential for capturing crop dynamics, including satellite imagery (e.g., Sentinel-2 for NDVI), meteorological data, and field-level data such as soil properties and management practices. A Convolutional Neural Network (CNN) serves as the primary feature extractor, enhanced with spatial and temporal attention mechanisms. This allows the model to dynamically assign greater importance to the most informative features, such as focusing on specific underperforming areas within a field (spatial attention) or prioritizing data from critical growth periods (temporal attention).

Dynamic Crop Growth Modeling via System Identification

To bridge the gap between abstract features and agronomic interpretability, a system identification layer translates the CNN's representations into a structured, dynamic model of crop growth using a state-space representation. The system's "state" (x) is a vector of latent physiological variables (e.g., biomass, leaf area index, water stress level) that are inferred rather than directly measured. The model consists of two core equations:

1. **State Equation:** $x_{t+1} = f(x_t, u_t)$ which describes how the internal crop state (x_t) evolves over time based on its previous state and external inputs (u_t) from the CNN.
2. **Observation Equation:** $y_t = g(x_t)$, which relates the unobservable internal state to measurable outputs.

Sequential Prediction with Bidirectional LSTM

The sequence of state vectors is processed by a Bidirectional Long Short-Term Memory (Bi-LSTM) network for the final yield prediction. LSTMs are ideal for modelling crop growth over an entire season (Hochreiter and Schmidhuber, 1997) due to their ability to oversee long-term dependencies in sequential data. The Bi-LSTM processes the sequence in both forward and backward directions simultaneously , allowing predictions to be informed by both past conditions and future context, which leads to more robust and accurate forecasts.The framework's primary innovation is its final stage, which provides actionable advice using a Mixture-of-Experts (MoE) architecture. This consists of a "gating network" and multiple specialized "expert" models, each of which is a Large Language Model (LLM) agent fine-tuned on a specific agronomic subdomain (e.g., irrigation, pest management). The gating network routes a query to the most relevant expert. To ensure recommendations are factually grounded, each agent is enhanced with Retrieval-Augmented Generation (RAG), enabling it to retrieve information from an external knowledge base before generating a response. This mitigates the risk of LLM "hallucinations," provides evidence-based advice, and addresses key barriers to AI adoption in agriculture.

CONCLUSIONS

This research presents an integrated pipeline that resolves the fundamental trade-off between predictive accuracy and model interpretability in agricultural AI. The primary contribution is the synergistic fusion of a high-performance deep learning architecture (CNN-Bi-LSTM) with a control-theoretic "glass-box" model derived from system identification. This combination aims to achieve both robust forecasting and dynamic, transparent insight into crop growth processes. Furthermore, the introduction of a RAG-enhanced Mixture-of-Experts layer represents a significant advance, translating abstract model outputs into clear, actionable, and expert-level directives for on-farm management.

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