CROP YIELD PREDICTION USING DEEP LEARNING AND REMOTE SENSING TECHNIQUES

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Introduction:

Agriculture plays a vital role in ensuring global food security and economic stability. Accurate crop yield prediction is essential for effective agricultural planning, resource management, and decision-making by farmers and policymakers. However, traditional yield estimation methods rely heavily on manual field surveys and historical data, which are time-consuming, costly, and often lack accuracy and real-time adaptability.

With the advancement of technology, remote sensing and artificial intelligence have emerged as powerful tools for modern agriculture. Satellite-based remote sensing provides large-scale, continuous monitoring of crop conditions, while deep learning techniques enable the extraction of complex patterns from high-dimensional data. By combining these technologies, it is possible to develop intelligent systems that can predict crop yield more accurately and efficiently.

This project proposes a crop yield prediction system using a hybrid deep learning approach that integrates Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal analysis. The system utilizes multisource data, including satellite imagery (MODIS), weather parameters, and soil information, to capture both spatial and temporal variations in crop growth.

The proposed solution aims to provide accurate, scalable, and real-time yield predictions, supporting precision agriculture and sustainable farming practices. By leveraging advanced AI techniques, the system helps improve productivity, reduce risks, and enable data-driven decision-making in the agricultural sector.

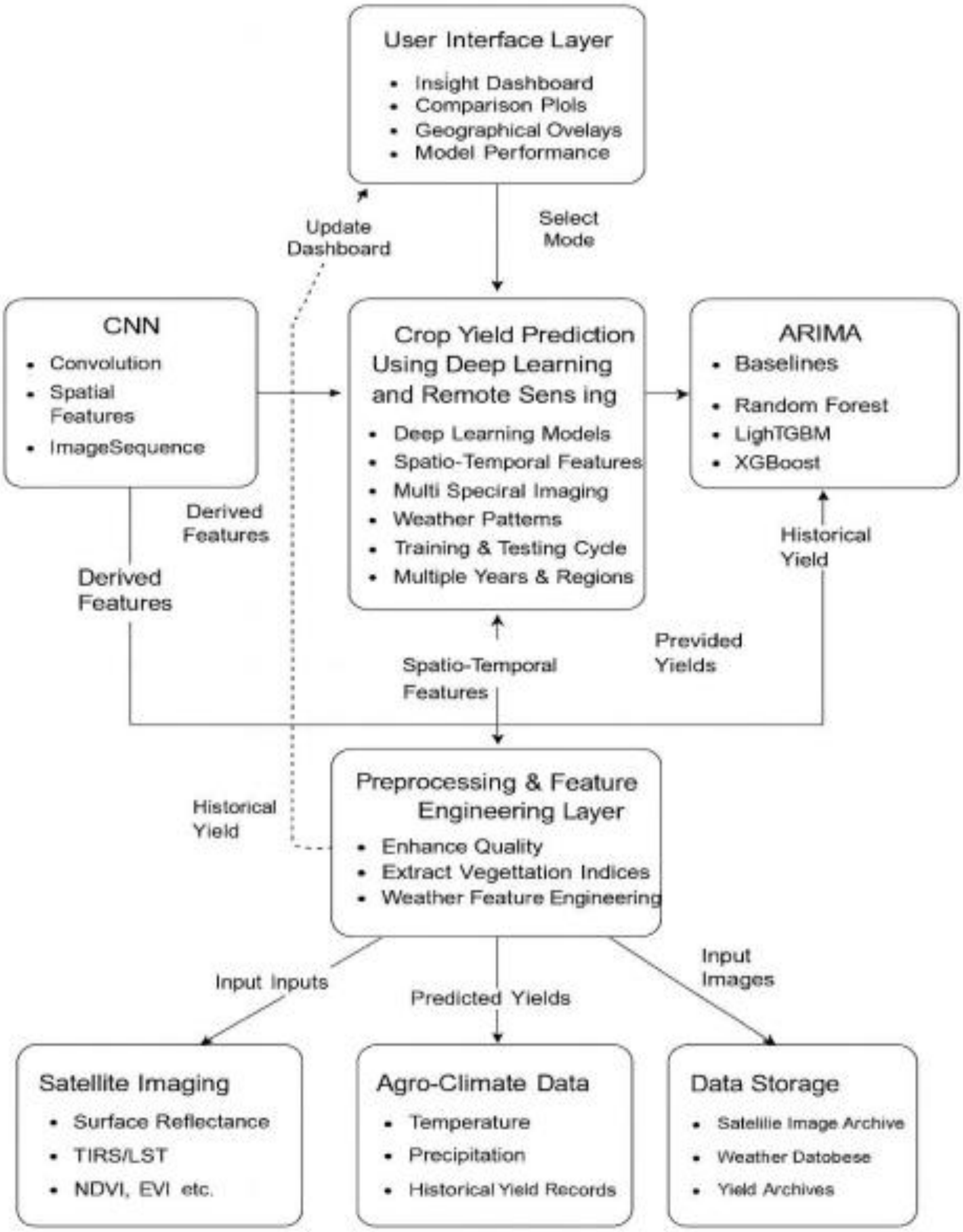

Figure 1: System Architecture of the Crop Yield Prediction System

Objectives:

1. To collect and preprocess multisource agricultural data including satellite imagery, weather, and soil parameters for accurate analysis.
2. To develop a hybrid deep learning model using CNN for spatial feature extraction and LSTM for temporal pattern analysis.
3. To improve prediction accuracy using advanced techniques such as data fusion, optimization, and model evaluation metrics like RMSE.
4. To build a scalable and user-friendly crop yield prediction system that provides real-time forecasting for precision agriculture.

Methodology:

1. **Data Collection:** Multisource agricultural data is collected, including satellite remote sensing data (MODIS), weather parameters (temperature, rainfall), soil data, and historical crop yield records from reliable sources.
2. **Data Preprocessing:** The collected data is cleaned, normalized, and aligned. Satellite images are resized and processed to extract vegetation indices (e.g., NDVI), while time-series data is structured and missing values are handled using interpolation techniques.
3. **Model Development (CNN-LSTM):** A hybrid deep learning model is developed where CNN extracts spatial features from satellite imagery and LSTM captures temporal dependencies in agricultural data. These features are combined to predict crop yield accurately.
4. **Model Training and Evaluation:** The model is trained using prepared datasets and evaluated using performance metrics such as RMSE, MAE, and R^2. The results are compared with traditional models like Random Forest and ARIMA to validate performance improvement.
5. **Prediction and Visualization:** The trained model is used to generate crop yield predictions, which are displayed through graphs, dashboards, and visual outputs for easy interpretation and decision-making.

Result and Conclusion:

The proposed crop yield prediction system using deep learning and remote sensing techniques demonstrated significant improvement over traditional statistical and machine learning models. The multivariate LSTM model achieved the lowest prediction error outperforming models such as Random Forest, LightGBM, XGBoost, and ARIMA. Additionally, the hybrid CNN-LSTM model effectively utilized satellite (MODIS) data along with agro-climatic parameters to capture both spatial and temporal patterns in crop growth, providing consistent and reliable predictions across different years.

The analysis revealed that key factors such as temperature, precipitation, fertilizer usage, and vegetation indices (e.g., NDVI) have a strong influence on crop yield. The system successfully identified seasonal trends, long-term variations, and environmental impacts, although slight performance degradation was observed during extreme climatic conditions like droughts.

Overall, the project demonstrates that integrating deep learning models with multisource data fusion significantly enhances prediction accuracy and supports data-driven decision-making in agriculture. The developed system contributes to precision agriculture by enabling real-time, scalable, and reliable yield forecasting. However, limitations such as dependence on moderate-resolution satellite data, limited regional validation, and reduced interpretability highlight the need for future improvements. Further work can focus on incorporating high-resolution satellite imagery, extending the model to multiple crops and regions, and improving robustness and explainability for practical deployment.

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Future Scope:

The future scope of this project includes:

1. **Advanced AI Models and Real-Time Deployment:** Implement advanced techniques such as attention mechanisms, transformers, and cloud-based real-time prediction systems to improve performance, interpretability, and practical usability.
2. **Extension to Multiple Crops and Regions:** Expand the system to support different crop types and diverse agro-climatic regions, making the model more scalable and widely applicable.
3. **Integration of High-Resolution Satellite Data:** Enhance prediction accuracy by incorporating higher-resolution satellite imagery (e.g., Sentinel data) to capture finer crop details and improve spatial analysis.