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School of Pure and Applied Science

Department of Computing and Informatics

**MACHINE LEARNING-BASED PREDICTIVE MODELLING FOR OPTIMIZING CROP YIELD UNDER CLIMATE VARIABILITY**

by

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1. ABSTRACT

Agriculture is crucial for global food security, yet it faces significant challenges due to climate variability. This proposal outlines a research project aimed at developing a machine learning-based predictive model to optimize crop yield. By analysing historical climate and crop yield data, the proposed model will predict future crop performance under varying Multivariate conditions. The major objective of the research work is to design a novel Multivariate Decision Support Model called Multivariate Hybrid Deep Learning Crop Yield Prediction (MHDLCYP) to collect a primary dataset on Multivariate conditions that influenced the crop yield and cultivations under different regions. The proposed model comprised of three phases wherein the novel integration methods to create a multivariate dataset is propounded. The pre-processing techniques is also developed as a novel model with techniques supporting all kinds of data. The training of model is performed by designing CNN-LSTM Hybrid Model for Crop Yield Prediction (CLHM-CYP) with CNN and RNN combination along with LSTM model for enhancement of dynamic knowledge in both spatial and temporal data respectively. The final phase develops a Decision Support System called Agricultural Crop Yield Decision Support System (ACY-DSS) that provides support to farmers in enhancing their cultivation methods. This research provides unique models and algorithms by combining multiple variant datasets in one dataset and also enhances the pre-processing and Training models by handling different types of data. The Outcome of the research will sustain the needs of the farmers in enhancing and monitoring their cultivation methods thereby creating a productive world for future generations.

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1. LIST OF ABBREVIATIONS

|  |  |  |
| --- | --- | --- |
| **S. No** | **Abbreviation** | **Meaning** |
| 1 | CNN | Convolutional Neural Network |
| 2 | LSTM | Long Short-Term Memory |
| 3 | DSS | Decision Support System |
| 4 | AI | Artificial Intelligence |
| 5 | ML | Machine Learning |
| 6 | DL | Deep Learning |
| 7 | RMSE | Root Mean Squared Error |
| 8 | MAE | Mean Absolute Error |
| 9 | MSE | Mean Squared Error |
| 10 | UI | User Interface |
| 11 | ReLU | Rectified Linear Unit |
| 12 | GPU | Graphics Processing Unit |
| 13 | IoT | Internet of Things |
| 14 | RNN | Recurrent Neural Network |
| 15 | SGD | Stochastic Gradient Descent |
| 16 | API | Application Programming Interface |

# SECTION 1. INTRODUCTION

Agriculture is a foundation of global food security, economic stability, and environmental sustainability. However, traditional farming methods often rely on empirical knowledge and experience, leading to suboptimal practices and reduced yields.

## Introduction to the Problem

The integration of Machine Learning (ML) into agriculture presents an opportunity to revolutionize farming by offering precise, data-driven recommendations. Agricultural productivity is essential for feeding the growing global population. However, climate variability poses a substantial risk to crop yields, making it imperative to develop adaptive strategies. Traditional methods of agricultural planning often fall short in anticipating the complex interactions between climate factors and crop performance. Machine learning offers a promising solution by enabling data-driven decision-making to enhance agricultural resilience and productivity. This research proposes to utilize advanced machine learning algorithms to predict the outcomes of various agricultural practices, thereby optimizing crop yields and resource usage.

## Background

Previous studies have demonstrated the potential of machine learning in agriculture, particularly in areas such as crop disease detection, soil health assessment, and climate impact analysis. However, existing models often focus on isolated factors rather than a comprehensive approach that integrates multiple variables. Furthermore, many studies have not fully explored the predictive capabilities of advanced ML models, such as deep learning and ensemble methods, in optimizing crop yields. The impact of climate change on agriculture has been extensively studied, revealing a direct correlation between climate variability and crop yield fluctuations. Previous research has employed statistical models to predict crop yields based on historical data. However, these models often lack the ability to capture non-linear relationships and complex interactions among multiple climate variables. Machine learning models, particularly deep learning, have shown superior performance in various predictive tasks due to their ability to learn intricate patterns from large datasets.

## Problem Statement

Farmers face numerous challenges in maximizing crop yields, including unpredictable weather patterns, soil degradation, and inefficient use of resources. Current decision-making processes are often reactive rather than proactive, leading to inefficiencies and wastage. There is a persistent need for a predictive system that can guide farmers in making informed decisions about planting, irrigation, fertilization, and pest control. Farmers need reliable tools to predict crop yields under changing climatic conditions to make informed decisions regarding planting, irrigation, and resource allocation. Existing predictive models are often too simplistic, failing to account for the dynamic and multifaceted nature of climate-crop interactions. This gap necessitates the development of advanced models that can provide accurate and timely predictions to support sustainable agricultural practices..

## General Objective

The general objective of this research is to develop Multivariate Hybrid Deep Learning Crop Yield Prediction (MHDLCYP) system that is capable of forming multivariate dataset based on different conditions like satellite maps, farmer reports, weather station data and soil data etc. The research work develops a novel Integrated Multivariate agriculture crop assistive dataset that is pre-processed using novel techniques. The hybrid Deep Learning model is designed to train and evaluate dataset as part of feature engineering process. Finally, a novel Agricultural Crop Yield Decision Support System (ACY-DSS) that provides support to farmers in enhancing their cultivation methods is developed with optimal solution to farming with maximisation of crop yields with consistent monitoring by developing a model and application software.

## Specific Objectives

Based on the general objectives and its future perspectives of achievement, some of the specific objectives are propounded. They are the following:

* To collect and preprocess a comprehensive dataset encompassing historical crop yields, soil health metrics, climate data, and agricultural practices.
* To develop and train advanced machine learning models that can predict crop yields based on the integrated dataset.
* To design and train a machine learning model capable of predicting crop yields based on climatic inputs.
* To evaluate the model's performance against existing predictive methods.
* To develop a user-friendly interface for farmers to access predictive insights.
* To evaluate the performance of different ML models and select the most accurate and reliable model for deployment.
* To create an optimal decision support system that provides actionable recommendations to farmers.

These specific objectives have to be achieved on course to achieve the overall objective of the research. The thrust area for the research is Machine Learning Predictions in Agricultural Climate variations.

## Hypothesis/Research Questions

On the basis of the research objectives proposed in the research, some of the hypothetical statements are recommended for testing during the course of research experiments. They are furnished below:

**Hypothesis-1:**

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**Hypothesis-2:**

**Hypothesis-3:**

These hypothetical statements are verified and analysed during the course of the research experiments and methodological Decision Support Systems.

### Research Questions

The overall research work also ponders some of the following research questions that has to be answered in course of the research. They are enumerated below:

1. How accurately can machine learning models predict crop yields based on historical climate data?
2. Which climatic variables are most significant in influencing crop yields?
3. Can the model be generalized to different crops and regions?
4. Which machine learning models are most effective in predicting crop yields based on a Multivariate dataset?
5. How do different environmental and agricultural variables impact the accuracy of crop yield predictions?
6. What are the key factors that influence crop yields, and how can they be optimized through predictive modelling?
7. How can the predictive model be effectively translated into an optimal decision support system for farmers?

Its customary that these research questions are to be answered and manipulated in course of the various experiments conducted in the research phases.

## Expected Outcomes

The research work comprised of three major phases with each phase depicting an activity to reach the overall objective of the research. At the completion of the research, the following outcomes could be expected to be achieved:

1. A Multivariate dataset of historical climate and crop yield information to be designed and created,
2. A validated machine learning model that predicts crop yields with high accuracy,
3. A comparative analysis of the model's performance against traditional methods,
4. A practical tool for farmers to use in agricultural planning,
5. Insights into the most influential climatic factors affecting crop yields,
6. A comprehensive dataset that integrates historical crop yields, soil health metrics, climate data, and agricultural practices,
7. A validated machine learning model capable of accurately predicting crop yields under various conditions,
8. A decision support system that provides actionable recommendations to farmers, leading to optimized agricultural practices and improved crop yields.

The expected outcomes of this research have the potential to significantly benefit farmers, policymakers, and researchers by offering a practical tool for improving crop yields and resource management.

## Justification of Study

The proposed research addresses a critical need in agriculture by providing a data-driven approach to optimize crop yields. By leveraging advanced machine learning techniques, this study aims to overcome the limitations of traditional farming practices and enhance the efficiency and sustainability of agricultural production. Additionally, this study will contribute to the broader field of precision agriculture, paving the way for future innovations and advancements. The increasing unpredictability of climate patterns poses a significant threat to global food security. By leveraging machine learning, this study aims to provide farmers with robust tools to navigate these challenges effectively. Accurate crop yield predictions will enable better resource management, reduce economic losses, and contribute to sustainable agricultural practices. This research will also advance the field of agricultural informatics by integrating cutting-edge machine learning techniques into practical farming applications.

# SECTION 2. LITERATURE REVIEW

The integration of machine learning (ML) into agriculture, particularly for optimizing crop yields, has garnered significant attention in recent research. This literature review examines various journal articles, providing a comprehensive overview of the current status of research, identifying existing research gaps, and justifying the research methods for developing a predictive crop yield optimization framework.

## Current Status of the Research Problem

Recent studies have explored various machine learning models for agricultural applications. Mousavi et al. (2024) [1] aimed to predict wheat yield in Southwest Iran using the FAO-Agro-Climate method and machine learning algorithms (MLAs). Soil samples and wheat grain data from Pasargad plain were analyzed. The study found that soil organic carbon (SOC) and total nitrogen (TN) significantly correlate with wheat yield. The study utilized random forest (RF) and artificial neural networks (ANNs) for mapping yield, with ANNs performing better (R² = 0.75). The study concludes that integrating crop models with MLAs can effectively predict yield gaps and improve agricultural productivity in similar regions. Eddamiri et al. (2024) [2] developed a web-based application for wheat yield prediction in Africa using an ensemble learning model. The model integrates various feature scaling algorithms and machine learning techniques based on meteorological and agricultural data. Gradient Boosting Regression (GBR) with MaxAbsScaler showed the highest accuracy (R² = 0.97), indicating the model's potential to aid farmers in decision-making and improving food productivity in North Africa. Tamayo-Vera et al. (2024) [3] highlights the use of machine learning (ML) and deep learning (DL) in agroclimatic studies, identifying a gap in methodology documentation which hampers replicability. The paper advocates for Automated Machine Learning (AutoML) to enhance research scalability and adaptability, suggesting that AutoML can significantly improve the development of sustainable agricultural practices in response to climate change.

Shingade and Mudhalwadkar (2024) [4] analyses various ML and DL approaches for crop prediction, discussing global demand and supply, and evaluating existing crop recommendation systems. The study highlights the strengths and weaknesses of different models and suggests that improved crop prediction models can be developed by addressing current challenges and leveraging diverse datasets and environmental factors. Wang et al. (2024) [5] introduces a framework combining Deep Reinforcement Learning (DRL) and Recurrent Neural Networks (RNNs) for optimal nitrogen fertilization management in corn crops. Using the Gym-DSSAT simulator, the research shows that policies developed under the framework adapt well to climate variability, improving crop yields and environmental sustainability. The need for policy adjustments under extreme weather events is also emphasized.

Gopi and Karthikeyan (2024) [6] presents the Red Fox Optimization with Ensemble Recurrent Neural Network (RFOERNN) model for crop recommendation and yield prediction. The model, which integrates LSTM, BiLSTM, and GRU, outperforms individual classifiers. The RFO algorithm optimizes hyperparameters, enhancing prediction accuracy. The model's effectiveness is validated using Kaggle datasets. Saravanan and Bhagavathiappan (2024) [7] proposes two crop yield prediction models based on 21 years of data: a machine learning model using CatBoost regression and a hybrid deep learning model combining spatio-temporal attention-based convolutional neural network (STACNN) and BiLSTM. Both models significantly outperform existing methods, with CatBoost achieving a slightly higher R² value of 0.99. Gadupudi et al. (2024) [8] utilizes deep learning for crop prediction, providing detailed information on soil attributes and their costs. By integrating LSTM and RNN strategies with ML techniques like SVM, the model offers precise yield predictions, aiding farmers in making informed business decisions based on climate and soil conditions. Du et al. (2024) [9] evaluates the accuracy of machine learning models in predicting cropland evapotranspiration (ET) across different climate zones. Models like RF, SVM, XGB, and BP showed significant accuracy, with variations based on climate conditions and input factors. The study emphasizes the importance of region-specific model selection for effective ET prediction. Stumpe et al. (2024) [10] examines the use of ML-based optical sensing for predicting pasture yield. It highlights the variety of vegetation indices, the emphasis on feature selection, and the need for consistent performance metrics reporting. The review suggests improving study design comparability to facilitate integration of findings and enhance model accuracy.

## Overview of Machine Learning Application in Agriculture for Climate Change Mitigation

Youssef et al. (2024) [11] evaluated the effectiveness of machine learning (ML) algorithms in predicting evapotranspiration (ETo) to enhance irrigation management. They utilized various ETo calculation methods (Penman-Monteith, Hargreaves, Blaney-Criddle) and ML models (SVR, RF, XGboost, KNN, DT, LR, MLR). The models achieved high accuracy with R² values up to 0.99 and low RMSE and MAE, indicating strong predictive capabilities. Zou et al. (2024) [12] improved the accuracy of maize yield simulations in China by downscaling Global Gridded Crop Models (GGCMs) using ML methods, notably Random Forest. Their enhanced models captured more variability in county-level yields and identified significant yield gaps due to suboptimal nitrogen management. Shevchenko et al. (2024) [13] utilized interpretable ML techniques to predict climate change impacts on agricultural land suitability in Central Eurasia. Their model achieved 86% accuracy and provided vital insights for policymakers to manage resources and enhance food security under different carbon emission scenarios. Xiao et al. (2024) [14] developed a hybrid approach integrating agricultural system modeling, ML, and life cycle assessment to optimize fertilizer application, irrigation, and residue management. This approach reduced resource requirements and greenhouse gas emissions in the North China Plain, demonstrating the benefits of spatiotemporal co-optimization for sustainable agriculture. Srivastava et al. (2024) [15] introduced a probabilistic framework for irrigation scheduling based on soil moisture, leaf area index, and evapotranspiration. They used a combination of Random Forest and Long Short-Term Memory models to predict irrigation needs, ensuring optimal water usage while minimizing waste. Kempelis et al. (2024) [16] applied computer vision and ML to predict relative air humidity, soil moisture, and light intensity in urban farming. Their models, particularly effective for humidity and soil moisture, highlight the potential of these technologies to enhance urban agricultural productivity and sustainability.

Qiao et al. (2024) [17] proposed a hybrid ML approach for early-season winter wheat yield forecasting. Their method, incorporating climate forecasts, provided accurate predictions up to eight months before harvest, giving stakeholders more time to manage crop yield risks. Huang et al. (2024) [18] used remote sensing and ML models (RF, CatBoost, XGBoost, LightGBM) to predict the global distribution of fall armyworm and its host plants. The ensemble models demonstrated high accuracy and indicated increasing threats to host plants due to climate change. Sarkar et al. (2024) [19] utilized advanced ML algorithms, including LSTM, Bi-LSTM, GPR, FIS, and ensemble techniques, to improve rice yield predictions at the ripening stage. These methods significantly enhanced the precision of yield forecasts. Veeramanju (2024) [20] reviewed AI and ML approaches in irrigation management, highlighting their potential to improve scheduling accuracy and sustainability. The study emphasized the importance of data-driven methods in optimizing irrigation practices and conserving water resources. Based on all these possibilities of models in agriculture and crop yielding mechanisms with different computer-based prediction models in Machine Learning and Deep Learning, the novel model could be developed.

## Identification of the Existing Research Gaps

Many existing studies focus on specific crops or regions, limiting the generalizability of their findings. Wang et al. (2024) [21] explored intelligent agricultural management systems that consider N₂O emissions and climate variability. The study addressed uncertainties and emphasized the need for adaptive strategies to optimize crop production while minimizing greenhouse gas emissions. Dey et al. (2024) [22] developed a machine learning-based recommendation system for agricultural and horticultural crops in India, considering NPK (nitrogen, phosphorus, potassium), soil pH, and climatic variables. Their model aids farmers in selecting suitable crops based on soil and climate conditions to enhance productivity. Sarkar et al. (2024) [23] used hybrid machine learning models to map groundwater potential in Bangladesh, considering climate variability. Their national-level study demonstrated the efficacy of ML in identifying regions with high groundwater potential, essential for sustainable water resource management. Banda et al. (2024) [24] estimated millet yields in Senegal by integrating regional water stress analysis with advanced predictive modelling. Their approach provided accurate yield predictions, highlighting the importance of water management in crop production under varying climatic conditions. Dhillon et al. (2024) [25] evaluated the impact of climate change on maize and soybean yields using ML models. Their findings indicated significant yield variability due to changing climate patterns, underscoring the need for adaptive agricultural practices to maintain crop productivity. Choudhury et al. (2024) [26] developed an optimized crop recommendation system using ML algorithms. The system considers multiple factors, including soil properties and climate conditions, to suggest the best-suited crops, thereby aiding farmers in decision-making and enhancing agricultural efficiency. Dotse et al. (2024) [27] reviewed the application of hybrid ML models in improving rainfall prediction. Their study highlighted the enhanced accuracy of hybrid models, which combine different ML techniques, providing better forecasts crucial for agricultural planning and water resource management. Calvo-Olivera et al. (2024) [28] proposed ML-based models to evaluate uncertainties in weather forecasts in real-time. Their approach improved the reliability of weather predictions, aiding farmers in making informed decisions based on more accurate climate information. Attri et al. (2024) [29] reviewed various ML applications in crop management, covering aspects like yield prediction, disease detection, and resource optimization. They concluded that ML techniques significantly enhance crop management practices, leading to improved agricultural productivity and sustainability. Tanaka et al. (2024) [30] assessed the accuracy of ML models in providing fertilizer recommendations. Their study demonstrated that ML models could offer precise fertilizer application strategies, optimizing nutrient use and enhancing crop yields. Some of the research gaps based on the analysis of all the above literatures are enumerated below:

1. Many studies focus on specific data types (e.g., soil properties, climate data), but integrating diverse data sources such as remote sensing, socioeconomic factors, and crop management practices remains underexplored. Comprehensive datasets could improve model accuracy and applicability across different regions.
2. Although some research addresses short-term climate variability, there is a need for studies that incorporate long-term climate projections. This would help in understanding and mitigating the impacts of climate change on agriculture over extended periods.
3. Most ML models are developed with large-scale farming in mind. There is a gap in research focused on adapting these technologies to smallholder farmers, particularly in developing countries where access to advanced technologies and data can be limited.
4. Real-time data processing and decision support systems are still in their infancy. Developing models that can process data in real-time and provide immediate recommendations to farmers could significantly enhance on-the-ground agricultural management.
5. Few studies have examined the economic viability and cost-benefit analysis of implementing ML-based agricultural practices. Understanding the economic implications is crucial for widespread adoption among farmers.
6. Current research often overlooks the impact of ML-driven practices on soil health and biodiversity. There is a need for studies that consider these environmental factors to ensure sustainable agricultural practices.
7. Many ML models are developed and tested on small scales or specific regions. Research is needed to test and refine these models for scalability, ensuring they can be effectively applied to larger and more diverse agricultural landscapes.
8. The gap between the development of ML technologies and their practical application by farmers remains significant. Research on effective education and training programs to bridge this gap is essential for maximizing the benefits of ML in agriculture.

Addressing these research gaps could enhance the effectiveness and adoption of ML technologies in agriculture, leading to more sustainable and resilient agricultural systems.

## Justification of the Study

The justification for this study lies in the pressing need to enhance agricultural productivity and sustainability in the face of numerous global challenges. Agriculture is the backbone of food security and economic stability for many countries, but it is increasingly threatened by climate change, resource limitations, and the growing global population. Traditional farming practices often fall short in addressing these multifaceted issues, necessitating innovative approaches that leverage advanced technologies. Machine learning (ML) presents a powerful tool to revolutionize agricultural management by offering precise, data-driven insights that can optimize crop yields, resource use, and environmental sustainability. This study is particularly justified for several key reasons:

1. Climate change poses significant threats to agricultural productivity through unpredictable weather patterns, temperature extremes, and altered precipitation. By utilizing ML to predict and adapt to these changes, farmers can make informed decisions that mitigate risks and enhance resilience.
2. Efficient management of water, fertilizers, and other inputs is crucial for sustainable agriculture. ML models can analyse vast amounts of data to provide precise recommendations on resource use, reducing waste and environmental impact while maximizing crop yields.
3. With the global population projected to reach 9.7 billion by 2050, ensuring food security is a critical challenge. ML can help increase agricultural productivity and efficiency, contributing to the global goal of feeding the growing population.
4. Smallholder farmers, particularly in developing countries, often lack access to advanced agricultural technologies. Research focused on adapting ML tools for these farmers can significantly improve their productivity and livelihoods, promoting equitable growth.
5. Traditional agricultural practices often rely on intuition and experience. ML introduces a data-driven approach that can provide more accurate and reliable recommendations, leading to better outcomes in crop management and overall farm performance.
6. Sustainable agricultural practices are essential for long-term environmental health. ML can aid in developing strategies that balance productivity with sustainability, ensuring that farming practices do not degrade soil health, water quality, or biodiversity.
7. Policymakers and stakeholders require robust data to formulate effective agricultural policies. ML-based insights can inform policy decisions, strategic planning, and the allocation of resources, helping to create a supportive environment for agricultural innovation.

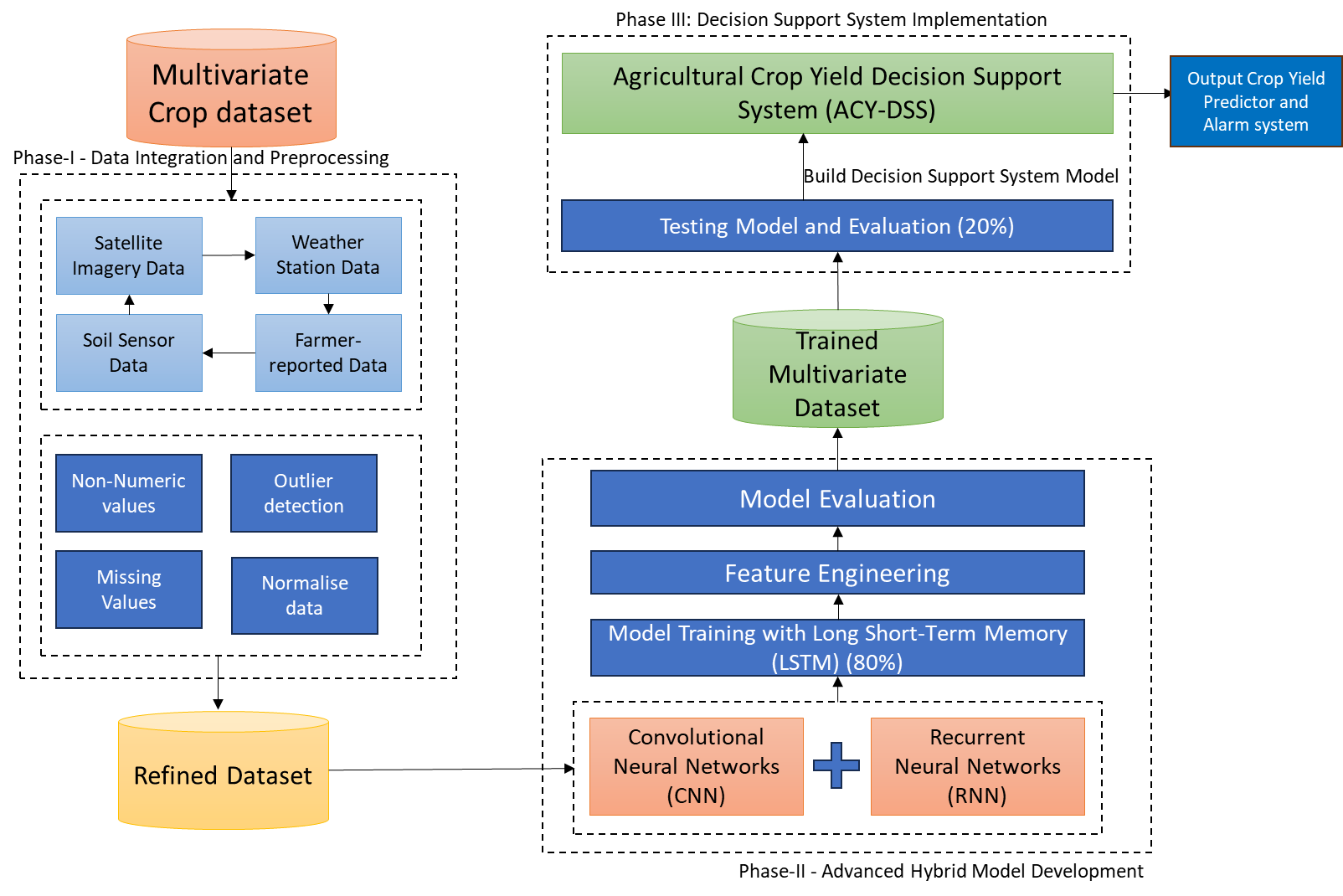
Overall, the integration of machine learning in agriculture is not just a technological advancement but a necessary evolution to meet the demands of a changing world. This study aims to explore and address the existing research gaps, providing a comprehensive understanding of how ML can be effectively utilized to transform agriculture for a sustainable and secure future.

# SECTION 3. THEORETICAL FUNDAMENTALS / METHODOLOGY

This research proposes a novel framework for optimizing crop yield predictions using advanced machine learning techniques. The framework is divided into three distinct phases: Data Integration and Preprocessing, Advanced Model Development, and Decision Support System Implementation. Each phase incorporates innovative approaches to address current limitations and improve the accuracy and applicability of crop yield predictions.

## Theoretical Framework

The research work designs a novel framework for enhancing agricultural activities by improving the dataset with different climatic variations. This model Multivariate Hybrid Deep Learning Crop Yield Prediction (MHDLCYP) Framework comprised of three major phases of work as given in Figure.1.

 **Figure.1. Overall Architecture of the proposed Multivariate Hybrid Deep Learning Crop Yield Prediction (MHDLCYP) Framework**

The overall research work as given in Figure.1., comprised of three major phases of study as presented in distinct heads.

## Phase 1: Data Integration and Preprocessing

The First phase propounds tocollect and integrate diverse datasets including historical crop yields, soil health metrics, climate data, and agricultural practices. The phase also pre-processes the data ensuring quality, consistency, and readiness for model development. Various models and techniques will be designed based on the achievement of objectives of the research work including collecting data from different sources including satellite imagery, weather stations, soil sensors, and farmer-reported databases. A novel model will be designed to utilise the multi-source data fusion approach to combine data from different sources. Various techniques were employed such as the Kalman filter for temporal data integration and Bayesian data fusion for probabilistic data integration. The general algorithm for phase-1 work is given in Table.1.

**Table.1. Algorithm Data Integration and Preprocessing Model (DIPM)**

|  |
| --- |
| **Algorithm** **Data Integration and Preprocessing Model (DIPM)** |
| **Begin**  **Input:** Satellite imagery data, weather station data, soil sensor data, farmer-reported data  **Output:** Integrated dataset  1. Initialize data sources  - satellite\_data ← load\_satellite\_data()  - weather\_data ← load\_weather\_data()  - soil\_data ← load\_soil\_data()  - farmer\_data ← load\_farmer\_data()  2. Integrate data sources  - integrated\_data ← initialize\_empty\_dataframe()  // Loop through each data source and merge based on timestamp and location  FOR each timestamp in satellite\_data:  satellite\_entry ← get\_entry(satellite\_data, timestamp)  weather\_entry ← get\_entry(weather\_data, timestamp)  soil\_entry ← get\_entry(soil\_data, timestamp)  farmer\_entry ← get\_entry(farmer\_data, timestamp)  integrated\_entry ← merge\_entries(satellite\_entry, weather\_entry, soil\_entry, farmer\_entry)  append(integrated\_data, integrated\_entry)  END FOR  Return integrated\_data |
| End DIPM |

As given in Table.1., Data Integration and Preprocessing Model (DIPM) is the initial novel process initiated in our research. The data preprocessing stage comprised of cleaning process that Implements data cleaning techniques to handle missing values, outliers, and noise. Also, K-Nearest Neighbours (KNN) is used as imputation for Missing Data and Z-Score normalization for outlier detection. The algorithm for data pre-processing has been presented in Table.2.

**Table.2. Algorithm Data Pre-Processing Model (DPPM)**

|  |
| --- |
| **Algorithm** Data Pre-Processing Model (DPPM) |
| **Begin**  **Input:** Integrated dataset  **Output:** Preprocessed dataset  FOR each column in integrated\_data:  IF column has missing values:  column ← impute\_missing\_values(column, method="KNN")  END IF  IF column has outliers:  column ← remove\_outliers(column, method="z-score")  END IF  END FOR  FOR each numeric column in integrated\_data:  column ← normalize (column, method="min-max")  END FOR  FOR each categorical column in integrated\_data:  column ← one\_hot\_encode(column)  END FOR  features ← []  FOR each column in integrated\_data:  IF column is numeric:  features.append(pca\_transform(column))  ELSE:  features.append(polynomial\_feature\_expansion(column))  END IF  END FOR  preprocessed\_data ← combine(features)  Return preprocessed\_data |
| **End** DPPM |

As given in Table.2., the Normalization and Transformation process includes normalizing continuous data using min-max normalization and transform categorical data using one-hot encoding. The Feature Engineering process includes extracting meaningful features from raw data using techniques such as Principal Component Analysis (PCA) for Dimensionality Reduction and Polynomial Feature Expansion for capturing non-linear relationships.

**Expected Outcomes:**

The expected outcomes of the first phase completion include the following:

* A comprehensive, integrated dataset that is clean, normalized, and feature-engineered, ready for advanced model development.
* Improved data quality and consistency, facilitating more accurate and robust machine learning models.

After completing phase-I of work, the second phase is initiated.

## Phase 2: Advanced Hybrid Model Development

The second phase begins to develop advanced machine learning models for predicting crop yields. It also leverages unique novel algorithms that can handle complex relationships and large datasets effectively. The model selection and training would be the important phase of the study. This phase develops unique novel Hybrid model CNN-LSTM Hybrid Model for Crop Yield Prediction (CLHM-CYP) that combined the Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks models to form a novel system. CNNs is used for analysing spatial data from satellite imagery to capture spatial patterns in crop health and yield. Also, another choice for DL models are the Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for handling sequential data like weather patterns and temporal soil moisture levels. Some of the machine learning Ensemble Learning models like Random Forest (RF) and Gradient Boosting Machines (GBM) are used for robust yield predictions by combining multiple weak learners to improve generalization. It is also important to test the dataset by creating hybrid models including CNN-LSTM Hybrid that integrates CNNs and LSTMs to leverage both spatial and temporal data for enhanced predictive performance. The overall algorithm for phase-II hybrid model creation is given in Table.3.

**Table.3. Algorithm CNN-LSTM Hybrid Model for Crop Yield Prediction (CLHM-CYP)**

|  |
| --- |
| **Algorithm:** CNN-LSTM Hybrid Model for Crop Yield Prediction (CLHM-CYP) |
| **Input:** Pre-processed dataset (images, temporal data, static features)  **Output:** Predicted crop yields  Initialize : = hyperparameters  :- num\_epochs ← 50  :- batch\_size ← 32  :- learning\_rate ← 0.001  :- num\_filters ← 64  :- filter\_size ← (3, 3)  :- lstm\_units ← 100  :- dense\_units ← 50  Initialize CNN model  FOR each image in the dataset:  :- image ← preprocess\_image(image)  :- Apply convolution layer with num\_filters and filter\_size  :- Apply ReLU activation function  :- Apply max pooling layer  :- Apply additional convolution and pooling layers if necessary  :- Flatten the output  :- Append flattened output to cnn\_features list  END FOR  Initialize LSTM model  :- FOR each sequence in the temporal data:  :- sequence ← preprocess\_sequence(sequence)  :- Apply LSTM layer with lstm\_units  :- Apply additional LSTM layers if necessary  :- Append LSTM output to lstm\_features list  END FOR  Hybridise cnn\_features and lstm\_features into combined\_features  :- Apply dense (fully connected) layer with dense\_units to combined\_features  :- Apply ReLU activation function  :- Apply dropout for regularization  :- Apply final dense layer to get predicted yields  Model <- Evaluate()  {  :- Define loss function : = Mean Squared Error  :- Define optimizer := Adam with learning\_rate  :- Compile the model with defined loss function and optimizer  }  FOR epoch in range(num\_epochs):  :- Shuffle the dataset  :- FOR batch in dataset with size batch\_size:  :- X\_batch, y\_batch ← get\_batch(batch)  :- Train the model on X\_batch and y\_batch  END FOR  END FOR  Evaluate the model on validation/test set  Compute performance metrics := RMSE, MAE  Return (trained model and performance metrics) |
| End CLHM-CYP |

As given in Table.3., the proposed CNN-LSTM hybrid model for crop yield prediction involves several detailed steps to ensure accurate and robust outcomes. The process begins with initializing key hyperparameters. These include setting the number of training epochs, batch size, learning rate, number of filters for the CNN layers, filter size, number of LSTM units, and the number of units in the dense layer. These parameters are critical as they define the model's structure and training process. In the first major phase, the CNN component of the model is defined. This phase starts by preparing a list to store features extracted from the CNN. Each image in the dataset undergoes preprocessing steps such as normalization and resizing to standardize input dimensions and values. Subsequently, the pre-processed image is passed through a convolutional layer, where the specified number of filters and filter size are applied. This convolutional layer detects important spatial features within the image. The output from this layer is then activated using the ReLU function, introducing non-linearity into the model. Following this, a max pooling layer is employed to reduce the spatial dimensions of the feature maps, making the computation more efficient. This sequence of applying convolution, ReLU activation, and max pooling can be repeated as needed to extract deeper spatial features. The final convolutional layer's output is flattened to create a one-dimensional feature vector, which is then stored in the cnn\_features list.

Parallelly, the LSTM component of the model is developed to handle temporal data. Similar to the CNN phase, a list is initialized to store LSTM-extracted features. Each sequence in the temporal dataset is pre-processed, often involving normalization and padding to ensure uniform sequence length. The pre-processed sequence is then fed into an LSTM layer, which captures temporal dependencies with the specified number of units. Additional LSTM layers can be added if necessary to capture more complex temporal patterns. The final output from the LSTM layers is stored in the lstm\_features list.

Once both CNN and LSTM features are extracted, they are combined into a single feature set termed combined\_features. This combined feature set is then processed through a dense layer with a specified number of units, where the ReLU activation function is applied to introduce non-linearity. To prevent overfitting, a dropout layer is added, which randomly drops a fraction of the units during training. Finally, a dense layer is applied to produce the predicted crop yields.

The model is then compiled with a chosen loss function, such as Mean Squared Error (MSE), which measures the difference between predicted and actual yields. An optimizer, like Adam, is employed with the pre-specified learning rate to adjust the model weights during training. The compilation of the model integrates these components to prepare for the training process.

During training, the dataset is shuffled at the beginning of each epoch to ensure random sampling. The dataset is divided into batches, and for each batch, the model is trained using the batch's input data (X\_batch) and corresponding labels (y\_batch). This iterative process continues for the specified number of epochs, allowing the model to learn and adjust its parameters progressively.

Upon completion of training, the model is evaluated using a validation or test set. Performance metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are computed to assess the model's predictive accuracy and robustness. These metrics provide insight into how well the model generalizes to unseen data.

Overall, the trained CNN-LSTM hybrid model, along with its performance metrics, is ready for application. This model leverages the spatial feature extraction capabilities of CNNs and the temporal sequence handling strengths of LSTMs to provide accurate crop yield predictions, making it a valuable tool in precision agriculture. The model has been optimised by setting the following tuning process as the end of the phase:

* **Hyperparameter Tuning** to utilisegrid search and random search techniques to optimize model hyperparameters.
* **Regularization** to apply techniques such as dropout in neural networks and L2 regularization to prevent overfitting.
* **Cross-Validation** to **i**mplement k-fold cross-validation to ensure model robustness and generalizability.

**Expected Outcomes:**

The expected outcomes of the first phase completion include the following:

* Development of high-accuracy machine learning models capable of predicting crop yields with greater precision.
* Enhanced understanding of the factors affecting crop yields through model interpretability techniques such as SHAP (SHapley Additive exPlanations).

After completing the second phase, the final phase of research will be performed.

## Phase 3: Decision Support System Implementation

The final phase implements the Agricultural Crop Yield Decision Support System (ACY-DSS) that translatespredictive model outputs into actionable insights for farmers. It also develops an optimal Decision Support System (DSS) that aids in practical agricultural decision-making. Based on the design of various components of the research DSS, the following outcomes are expected to be achieved at the end of the design:

* Generate detailed reports on expected yields under different scenarios and recommend optimal farming practices.
* Provide insights on efficient resource usage (e.g., water, fertilizers) to maximize yields and sustainability.
* Implement an alert system to notify farmers of potential issues such as pest outbreaks or adverse weather conditions.
* A functional Decision Support System that empowers farmers with data-driven insights and recommendations.
* Improved farm management practices leading to increased crop yields and resource efficiency.
* Enhanced ability to respond to environmental changes and mitigate risks through proactive decision-making.

The proposed framework aims to significantly enhance crop yield predictions and practical agricultural decision-making through a structured approach integrating data collection, advanced machine learning models, and a user-friendly DSS.

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