Journal of Computer Science

Research Article

Integrated ARIMA and Multi-Scale GRU for Crop Recommendation and Yield Prediction in Precision Agriculture

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Article history
Received: 08-05-2025
Revised: 31-05-2025
Accepted: 11-06-2025

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Abstract: Agriculture is the fundamental source of food, income, and livelihood for rural communities in India. Numerous crops are affected due to the lack of technical decision-making support and variations in weather patterns, temperature, rainfall, and atmosphere factors, which play a critical role in defining crop yield. Hence, choosing the appropriate crop to maximize yield is key to enhancing real-time farming practices. This study proposes an Auto-Regressive Integrated Moving Average (ARIMA) and Multi-Scale Gated Recurrent Unit (MSGRU) model for effective crop yield prediction and crop recommendation. Initially, label encoding and min-max normalization techniques are applied during the pre-processing phase to transform categorical values into uniform, numerical format for data scaling. Then, ARIMA is employed for crop yield prediction, followed by the MSGRU network deployed to extract both short-term and long-term dependencies, enabling accurate crop recommendation. The proposed ARIMA–MSGRU model achieves a superior accuracy of 99.73% at a reduced RMSE of 1.568, outperforming existing algorithms, demonstrating greater effectiveness.

Keywords: Auto Regressive Integrated Moving Average, Crop Recommendation, Crop Yield Prediction, Label Encoding, Min-max Normalization, Multi-Scale Gated Recurrent Unit

Introduction

Agriculture is an essential segment for ensuring food security and promoting sustainable growth in all countries (Thorat *et al.*, 2023). However, food insecurity remains a challenge in developing countries due to the inefficient management of food supply chains and poor harvests (Kiruthika and Karthika, 2023; Nti *et al.*, 2023; Reyana *et al.*, 2023; Chang *et al.*, 2024). Additionally, unsustainable agricultural practices negatively impact the environment and contribute to climate change. There is a growing need to enhance agricultural practices to ensure long-term sustainability (Senapaty *et al.*, 2024). Therefore, identifying appropriate crops to maximize production and yield is essential for meeting the increasing global food demand (Di *et al.*, 2022). The primary objective of collecting and integrating agricultural data from various regions is to estimate crop yields and identify optimal crops (Elbasi *et al.*, 2023). Crop Yield Prediction (CYP) relies mainly on two significant feature groups. The first set included factors such as land utilization, irrigation techniques, land preparation, and fertilizer usage, which were based on farmers' practices. The second set comprises environmental attributes, such as temperature, rainfall, and solar radiation, which are governed by natural conditions (Oikonomidis *et al.*, 2022).

A Crop Recommendation System (CRS) is a computer-enabled tool that supports farmers in making decisions about crop selection based on parameters such as weather patterns, historical crop yields, and soil type (Gupta *et al.*, 2022; Shams *et al.*, 2024). Recently, Machine Learning (ML) algorithms have been widely utilized in various areas of agricultural analysis, including yield prediction, crop selection, pattern detection, soil classification, disease detection, individual crop identification, and feature crop selection (Abdel-salam *et al.*, 2024). Rather than solely focusing on developing multiple ML algorithms to maximize prediction accuracy, spatial and temporal non-stationarity, which is critical in numerous geographic conditions, has been incorporated into agricultural productivity models (Nagesh *et al.*, 2024). Recently, Deep Learning (DL) algorithms have been employed to develop various advanced models used for selecting appropriate crops when multiple choices are available (Ahmed, 2023). This category of ML utilizes multiple layers in neural networks to learn from data and establish relationships between input and response variables to perform accurate predictions (Zhang *et al.*, 2025).

The novelty of the developed approach lies in the integration of ARIMA for efficient yield prediction with the proposed Multi-Scale Gated Recurrent Unit (MSGRU) network, which captures diverse temporal dependencies, short-term fluctuations, seasonal patterns, and long-term trends. Unlike traditional GRU or LSTM architectures, the multiscale structure significantly improves the model's capability of learning from heterogeneous agricultural data. This hybrid algorithm enhances the prediction accuracy and reduces the error rates across multiple performance metrics.

While Deep Learning (DL) algorithms like LSTM and GRU have enhanced temporal modeling, they still suffer from limited capability in handling multi-scale patterns, which are essential in agriculture due to seasonal effects, short-term anomalies, and long-term climatic trends. Similarly, statistical models, such as ARIMA, are efficient for stationary time-series forecasting but lack the ability to handle complex nonlinearities.

Hence, this article proposes a hybrid framework that integrates ARIMA for accurate time-series forecasting and MSGRU to model diverse temporal dependencies. The integration of statistical and DL methods enables the system to capitalize on the benefits of both algorithms, such as the interpretability of ARIMA and the learning capability of MSGRU, addressing the gap in capturing multi-scale dynamics for crop yield prediction and recommendation. This integrated framework is essential for developing robust and generalizable decision-support systems that can adapt to varying regional conditions, seasonal variability, and data heterogeneity.

Problem Statement

Agriculture in India is highly affected by unpredictable weather patterns and a lack of technical decision-making support, resulting in suboptimal crop selection and low yields. Current ML-based approaches often treat crop recommendation and yield prediction as separate problems, lacking the integration required for precise real-time decision-making. Additionally, existing algorithms struggle to efficiently capture multi-scale temporal dependencies in agricultural data, leading to reduced prediction accuracy and inconsistent recommendations.

This study addresses two interconnected agricultural tasks, crop yield prediction and crop recommendation, which are informed by distinct empirical variables derived from specialized datasets. The Crop Recommendation Dataset (CRD) encompassing key environmental and soil parameters including rainfall, humidity, pH levels, temperature, and concentrations of potassium, phosphorus, and nitrogen. Additionally, the Crop Yield Prediction Dataset (CYP) containing agricultural management variables such as cultivation area, geographical location (state and district), crop type, historical production data, seasonal patterns, and crop year information.

Objective

This study aimed to develop a hybrid ARIMA-MSGRU method that integrates time-series forecasting and deep learning for precise crop yield prediction and efficient crop recommendation. The objective is to improve the model's prediction performance by capturing both short- and long-term dependencies in the data using a multi-scale GRU structure, supporting farmers in choosing suitable crops to increase yield under varying climatic and agronomic conditions.

Contributions of the Study

The primary contributions of this study are outlined as follows. In the preprocessing phase, label encoding and min-max normalization techniques are utilized to transform categorical data into numerical values and scale them within a uniform range, thereby enhancing the model performance.

The Auto-Regressive Integrated Moving Average (ARIMA) algorithm is employed for accurate crop yield prediction, contributing to improved overall model performance.

The Multi-Scale Gated Recurrent Unit (MSGRU) is developed in the classification phase to capture both short- and long-term dependencies, enabling effective crop recommendations.

Research Findings

Research findings indicate that the proposed ARIMA–MSGRU method effectively enhances the accuracy and reliability of crop yield prediction and crop recommendation. Evaluation on two datasets shows that the method achieves a high recommendation accuracy of 99.73% and outperforms existing methods such as LSTM, GRU, RNN, and WTDCNN. For yield prediction, the method achieves a lower RMSE of 0.1664 and MAR of 0.2582, demonstrating superior forecasting ability over traditional algorithms like ARIMA. The MSGRU architecture captures short-term fluctuations, seasonal trends, and long-term dependencies in the data, which improves overall model performance. Moreover, the consistent results of the method highlight its generalization ability and robustness, making it suitable for different agricultural contexts.

Literature Review

Gopi and Karthikeyan (2023) proposed a Hybrid Moth Flame Optimization–Machine Learning (HMFO-ML) approach. The proposed technique effectively recommended crops and accurately predicted crop yield. It employed a Probabilistic Neural Network (PNN) for crop recommendation and an Extreme Learning Machine (ELM) technique for yield prediction. Additionally, the HMFO approach was integrated to enhance the prediction rate of the ELM algorithm. However, the method failed to capture long-term and multi-scale temporal dependencies, which were essential for accurate crop yield prediction.

Gopi and Karthikeyan (2024) developed a Red Fox Optimization with an Ensemble Recurrent Neural Network for Crop Recommendation and Yield Prediction (RFOERNN-CRYP) method. The approach followed an ensemble learning procedure and utilized three different DL algorithms, Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and GRU to improve prediction performance. Additionally, an RFO algorithm was employed for hyperparameter tuning to enhance overall model performance. However, the method treated crop yield prediction and crop recommendation as separate tasks, which led to inconsistencies in decision-making.

Subramaniam and Marimuthu (2024) presented a method comprising three stages: pre-processing, dimensionality reduction (DR), and classification. Firstly, agricultural data from a South Indian area was gathered from a dataset. Pre-processing was employed for data cleaning and normalization. Then, DR was performed using Squared Exponential Kernel-enabled Principal Component Analysis (SEKPCA). Finally, Crop Yield Prediction (CYP) was carried out using a Weight-Tuned Deep Convolutional Neural Network (WTDCNN), which predicted high crop yield profitability. However, the method struggled with non-stationary time-series data, which was common in agricultural scenarios due to changing climate patterns and seasonal variations.

Bhimavarapu *et al.* (2023) suggested a model for predicting crop yield with high accuracy. The integration of Deep Learning (DL) algorithms with crop statistics enabled precise yield rate predictions. An Improved Optimizer Function (IOF) was introduced to enhance prediction accuracy and was incorporated with an LSTM network. However, the conventional LSTM reduced its generalization ability across various regions or crop types due to overfitting or imbalanced agricultural datasets.

Hasan *et al.* (2023) conducted a study focused on a developing country like Bangladesh, where the economy heavily depended on agriculture. Initially, data were collected and pre-processed from research institutions in Bangladesh. An ensemble Machine Learning (ML) algorithm was then developed by integrating K-Nearest Neighbour (K-NN), Random Forest (RF), and Ridge Regression (RR) to efficiently predict primary crops. The KRR model was formulated after evaluating five existing conventional ML approaches, including Support Vector Regression (SVR), Naïve Bayes, Ridge Regression, and an ensemble of Random Forest and CatBoost techniques. These methods treated all temporal data equally and failed to distinguish between short-term and long-term trends, which reduced prediction accuracy.

The existing algorithms primarily focused on predicting crop yield using ML techniques, rather than crop selection. Existing studies faced challenges when dealing with multiple classes in crop prediction. Selecting the appropriate crop to maximize yield played a significant role in enhancing real-time farming outcomes. To mitigate this, this manuscript introduced an ARIMA model combined with a MSGRU network for effective yield prediction and crop recommendation.

Synthesis of Supporting Literature

Several previous studies synthesize the limitations of existing crop prediction methods and motivate the development of the ARIMA–MSGRU framework. For example, Gopi and Karthikeyan (2023) introduce an HMFO-ML algorithm that integrates PNN and ELM approaches. It obtains high accuracy in crop recommendation and yield prediction but fails to capture long-term and multi-scale temporal dependencies. Similarly, Gopi and Karthikeyan (2024) develop RFOERNN-CRYP by utilizing LSTM, Bi-LSTM, and GRU; these tasks of yield prediction and recommendation are processed separately, resulting in inconsistencies. These limitations in existing algorithms show the need for a more combined, temporally aware, and generalizable model. This motivates the present article to adopt a hybrid framework, integrating ARIMA (for statistical modeling of yield trends) and MSGRU (for learning multi-scale dependencies in crop recommendation) by addressing these gaps.

Model Selection

Models for this research are chosen to handle time-series agricultural data with complex, multi-scale temporal dependencies. The ARIMA model is selected for its effectiveness in predicting non-stationary time series data, making it suitable for crop yield prediction. The MSGRU network is developed to capture short-term fluctuations, seasonal patterns, and long-term trends in agricultural data. This hybrid selection, statistical ARIMA for yield prediction and MSGRU for crop recommendation, ensures enhanced accuracy, generalization, and robustness over traditional single approaches.

Proposed Method

In this manuscript, crop recommendation and yield prediction are performed using DL algorithms. Crop Recommendation Data (CRD) and Crop Yield Prediction (CYP) datasets are utilized. During the pre-processing phase, label encoding and min-max normalization techniques are applied to transform categorical data into numerical format and scale the values within a uniform range. Yield prediction is carried out using the ARIMA model, followed by the application of the developed MSGRU method to recommend suitable crops. Figure 1 illustrates the process of crop recommendation and yield prediction.

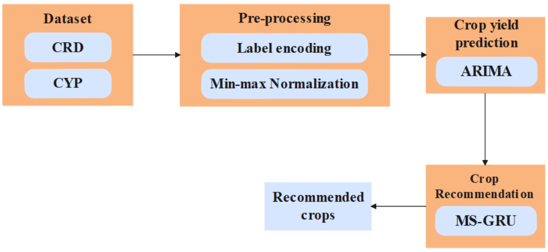

Fig. 1: Process of crop recommendation and yield prediction

Dataset

The datasets used in this study are: Crop Recommendation Data (CRD) and Crop Yield Prediction (CYP) datasets. A detailed description of these datasets is provided below.

Crop Recommendation Data

The CRD dataset contains a total of 2000 samples, utilizing rainfall, fertilizer, and climate data. The various classes in the dataset include moth beans, coconut, rice, kidney beans, apple, chickpea, orange, blackgram, pomegranate, mungbean, jute, banana, pigeon peas, lentil, watermelon, mango, grapes, maize, coffee, papaya, and cotton.

Crop Yield Prediction (CYP) Dataset

The CYP dataset includes samples across multiple crop classes of Moong (Green Gram), Urad, Rice, Maize, and Groundnut. The attributes included in this dataset are: Production, State_Name, District_Name, Crop_Area, Crop_Year, and Season.

Pre-Processing

The data were pre-processed using label encoding and min-max normalization algorithms to improve data quality. A detailed description of these techniques is provided below.

Label Encoding

This technique transforms categorical data into numerical format. In the dataset, the crop names are represented as strings. Label encoding is applied to convert these categorical variables into corresponding numerical values.

Min-Max Normalization

Since the dataset is unstructured and contains noise, min-max normalization is applied to each feature. The mathematical expression for this normalization is given in Eq. (1).

$$\hat{x}_i = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{1}$$

In the above Eq. (1), $\hat{x}_i$ is the normalized value, x_i represents the actual value, x_i^{min} is the minimum value of feature i and x_i^{max} is the maximum value of feature i. All features are scaled within the range of [0,1]. Normalization is essential because the target variable is predicted based on features with varying scales.

Auto Regressive Integrated Moving Average (ARIMA)

Particularly in time series analysis, ARIMA is a generalization of the Auto Regressive Moving Average (ARMA) methods. ARIMA methods are employed when the data series exhibit non-stationarity. The process involves determining the appropriate level of differencing to transform the series into a stationary form. The data series be denoted as x_t, where t represents the integer index. The ARIMA method is expressed in Eqs. (2) and (3).

$$X_t - \alpha_1 \cdot X_{t-1} - \ldots - \alpha_p \cdot X_{t-p'} = \epsilon_t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} \tag{2}$$

$$\left(1 - \sum_1^{p'} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \epsilon_t \tag{3}$$

In the above Eq. (3), L represents the lag operator, α_i represents the parameters of autoregressive phase of the model, θ_i represents the parameters of the moving average phase, and ϵ_t represents random error terms, where $\epsilon_t \sim iid\left(0, \sigma^2\right)$, indicating that the errors are self-determining and similarly distributed (iid), sampled from normal distribution with mean zero and unit variance. The series is differentiated d times to make it stationary as mathematically expressed in Eq. (4).

$$\left(1 - \sum_1^{p'} \alpha_i L^i\right) (1 - L)^d X_t = \left(1 - \sum_1^{p'-d} \phi_i L^i\right) (1 - L)^d \tag{4}$$

Where, $ARIMA\,(p, d, q)$ process involves the polynomial factorization properties $p = p'$ and the mathematical expression is as given in Eq. (5).

$$\left(1 - \sum_1^{p} \phi_i L^i\right) (1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \epsilon_t \tag{5}$$

This represents the $ARIMA\,(p, d, q)$ process with polynomials having d unit roots. The above Eq. (5), is generalized to accounting the drift term, as given in Eq. (6).

$$\left(1 - \sum_1^{p} \phi_i L^i\right) (1 - L)^d X_t = \sigma + \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \epsilon_t \tag{6}$$

In above Eq. (6), $\frac{\sigma}{(1 - \sum \phi_i)}$ is the drift term that represents the $ARIMA\,(p, d, q)$ process with a drift. The variance in Eq. (6) represents the difference among consecutive values of time series, where $y^{'} = y_t - y_{t-1}$ denotes the initial variance of the series, which accounts for large-order variance if necessary. The impulse Indicator Saturation (IIS) method, used to account for abrupt changes in the time series, is adjusted accordingly. Consider X_t as the series of interest, and the impulse indicators are given in Eq. (7).

$$I_{it} = \begin{cases} 1 & if\ t = t_i \\ 0 & otherwise \end{cases} \tag{7}$$

In the above Eq. (7) , t i represents a time when i t h exogenous variables affect endogenous variables. In the above Eq. (7), t_i represents a time when i^{th} exogenous variables affect endogenous variables.

GRU for Crop Recommendation

GRU is an extended version of Recurrent Neural Network (RNN), that is majorly employed due to its improved performance on time series prediction. The GRU effectively handles the issue of vanishing gradients, while retaining past data dependencies. When compared to LSTM, the GRU has a simpler architecture with fewer factors and faster training. The cell structure of the GRU is illustrated in Figure 2.

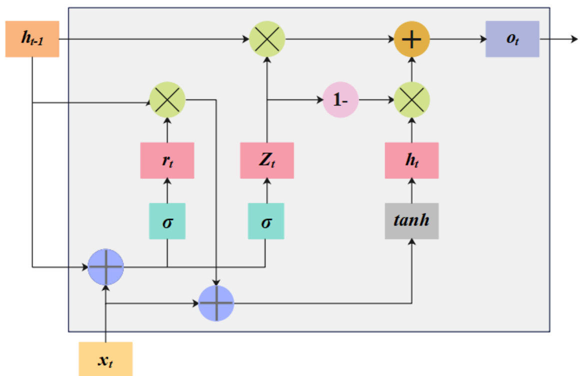

Fig. 2: The cell structure of GRU

The internal structure of GRU retains the state of past data through self-connections, enabling it to learn complex attributes and historical patterns. GRU employs two primary gates: the reset and update gate for processing sequential data. The reset gate determines the extent to which the past information should be forgotten and the update gate is utilized for determining the retention and removal of past data and present temporal information. Consider time series data with n instances, represented as $X = \{x_t | t = 1, 2, \ldots n\}$. The mathematical expression for calculating the reset gate is given in Eq. (8).

$$R_t = f\left(W_R \cdot [h_{t-1},\ x_t] + b_R\right) \tag{8}$$

In the above Eq. 8, h_{t-1} represents the past data at the time $t-1$. The mathematical expression for the update gate is given as Eq. (9).

$$U_t = f\left(W_U . [h_{t-1},\ x_t] + b_U\right) \tag{9}$$

Using R_t, the mathematical expression for computing the candidate state is measured in Eq. (10).

$$I_t = \tanh\left(W_I . [R_t \times h_{t-1},\ x_t] + b_I\right) \tag{10}$$

In the above Eq. 10, $\times$ represents elementwise multiplication, which serves as a linear interpolation between the past hidden state h_{t-1} and candidate state I_t. The mathematical expression for output gate of GRU is given in Eq. (11).

$$h_t = U_t \times I_t + (1 - U_t) \times h_{t-1} \tag{11}$$

In above Eq. (11), W_R, $W_U$and W_I represent the weights of reset, update and candidate states. In accordance with b_R, b_U and b_I represent the bias vectors of reset, update and candidate states, $f(\cdot)$ represents the sigmoid function and $\tanh(\cdot)$ is a hyperbolic tangent function.

Multiscale GRUMultiscale GRU

The traditional GRU processes time-series data but considers all past data uniformly. However, agricultural data have multi-scale temporal patterns, such as temperature fluctuations, sudden rainfall changes, seasonal effects, variations in soil moisture, impact of fertilizer, climate change trends, soil degradation, and previous crop yields. Here, a single GRU network struggles to capture all dependencies simultaneously. The Multiscale GRU (MSGRU) framework mitigates this problem using individual GRU layers for various time scales. The architecture of the MSGRU is shown in Figure 3.

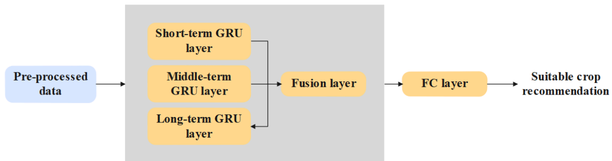

Fig. 3: Architecture of MSGRU

The MSGRU network includes three GRU layers in parallel. The initial GRU layer captures short-term dependency and rapid fluctuations. The middle GRU layer captures the seasonal trends. The final GRU layer captures the historical yield trends.

Finally, all three GRU layers are integrated using a fusion of concatenations. The mathematical expression for concatenation fusion is given as Eq. (12).

$$H_{final} = [h_{ST},\ h_{MT},\ h_{LT}] \tag{12}$$

In the above Eq. 12, H_{final} represents the final fusion layer, h_{ST} represents the outcomes of short-term GRU layer, h_{MT} represents the outcomes of middle-term GRU layer, and h_{LT} represents the outcomes of the long-term GRU layer.

Research Implications

This research presents significant implications for the application of deep learning (DL) algorithms in precision agriculture. By combining ARIMA with the Multi-Scale GRU, it demonstrates how integrating statistical forecasting with deep temporal learning enhances the accuracy of yield prediction and crop recommendation. It emphasizes the importance of multi-scale temporal modeling in agricultural datasets and paves the way for future work to adopt similar hybrid strategies in other time-series domains. Moreover, this research contributes to the advancement of intelligent decision-support systems for farmers, promoting the development of AI-driven agricultural tools that are adaptable to both regional and global farming challenges.

Experimental Results

The performance of ARIMA-MSGRU was simulated in a Python 3.7 environment with the following system configurations: an i5 processor, Windows 10 (64-bit), and 8GB of RAM.

The evaluation metrics considered to analyze the ARIMA-MSGRU method were accuracy, precision, F1-score, recall, and specificity for crop yield recommendation. Additionally, Mean Squared Error (MSE), Root MSE (RMSE), Mean Absolute Error (MAE), and $R2$ are considered. In Table 1, the performance of the ARIMA-MSGRU method is validated on different metrics on the Crop Recommendation dataset. The existing prediction algorithms namely, Exponential Smoothing (ETS), Vector Auto Regression (VAR), Auto Regressive Conditional Heteroskedasticity (ARCH), and Generalized ARCH (GARCH) are considered to evaluate crop recommendation. The developed ARIMA-MSGRU method achieves 99.73% accuracy, 99.46% recall, 99.21% precision, 99.33% F1-score, and 98.82% specificity when compared with existing algorithms.

Table 1: Performance of Crop Recommendation process on Crop Recommendation Dataset

Methods	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Specificity (%)
ETS	98.31	98.03	97.84	97.93	97.21
VAR	98.62	98.29	98.07	98.17	96.75
ARCH	98.93	98.64	98.32	98.47	97.27
GARCH	99.24	99.15	99.02	99.08	97.63
ARIMA - MSGRU	99.73	99.46	99.21	99.33	98.82

In Table 2, the performance of the ARIMA-MSGRU method is validated on the following error metrics on the crop recommendation dataset. Existing prediction algorithms such as ETS, VAR, ARCH, and GARCH are considered to evaluate the crop recommendation process. The ARIMA-MSGRU method obtains a less MSE of 0.0277, RMSE of 0.1664, R^2 of 0.8542, and MAE of 0.2582, when compared to existing algorithms.

Table 2: Performance of Crop yield prediction process on Crop Recommendation Dataset

Methods	MSE	RMSE	R^2	MAE
ETS	0.1231	0.3508	0.9378	0.3237
VAR	0.0985	0.3138	0.9137	0.3094
ARCH	0.0831	0.2882	0.8934	0.2914
GARCH	0.0427	0.2066	0.8721	0.2783
ARIMA - MSGRU	0.0277	0.1664	0.8542	0.2582

In Table 3, the performance of the ARIMA–MSGRU method is evaluated using various performance metrics on the Crop Yield Prediction dataset. Existing deep learning models such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), traditional GRU, and conventional MSGRU are considered for comparison in the crop yield prediction process. The developed ARIMA–MSGRU method achieves an accuracy of 99.73%, recall of 99.46%, precision of 99.21%, F1-score of 99.33%, and specificity of 98.82%, outperforming the existing algorithms.

Table 3: Performance of Crop recommendation process on Crop Yield Prediction Dataset

Methods	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Specificity (%)
RNN	96.82	96.69	96.32	96.50	96.18
LSTM	97.03	96.94	96.77	96.85	96.54
GRU	97.68	97.41	97.16	97.28	97.05
MSGRU	98.32	98.05	97.83	97.93	98.21
ARIMA - MSGRU	99.23	99.06	98.61	98.83	98.77

In Table 4, the performance of the ARIMA–MSGRU method is validated using multiple performance metrics for the Crop Yield Prediction dataset. Existing deep learning algorithms such as RNN, LSTM, traditional GRU, and conventional MSGRU are considered for comparison. The ARIMA–MSGRU method achieves a Mean Squared Error (MSE) of 0.0246, Root Mean Squared Error (RMSE) of 0.1568, coefficient of determination R^2 of 0.8472, and Mean Absolute Error (MAE) of 0.2328, demonstrating improved performance over existing algorithms. Table 5 presents the results of k-fold cross-validation for the proposed approach, while Table 6 reports the evaluation of computational time and memory usage.

Table 4: Performance of Crop Yield Prediction process on Crop Yield Prediction Dataset

Methods	MSE	RMSE	R^2	MAE
RNN	0.0407	0.2017	0.9371	0.2883
LSTM	0.0392	0.1979	0.9135	0.2814
GRU	0.0371	0.1926	0.8917	0.2783
MSGRU	0.0295	0.1717	0.8792	0.2617
ARIMA - MSGRU	0.0246	0.1568	0.8472	0.2328

Table 5: Performance of K-fold validation for proposed approach

K-values	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Specificity (%)
K=2	97.83	97.21	96.93	97.06	97.34
K=3	98.10	97.69	97.24	97.46	97.77
K=4	98.78	98.23	97.82	98.02	98.15
K=5	99.23	99.06	98.61	98.83	98.77

Table 6: Evaluation of computational time and memory usage

Methods	Computational time (s)	Memory Usage (MB)
RNN	189	119
LSTM	193	125
GRU	216	131
MSGRU	257	137
ARIMA - MSGRU	284	146

Results Interpretation

In the Crop Recommendation Dataset (CRD), input variables include Potassium (K), Phosphorus (P), Nitrogen (N), Temperature, pH, Rainfall, and Humidity. The proposed method demonstrates that Potassium, Phosphorus, and Nitrogen have a strong influence on the crop selection process, as these nutrients directly affect soil fertility and plant growth.

Temperature and Humidity are also essential variables captured by the MSGRU layers for modeling seasonal crop suitability. The short-term GRU layers effectively respond to rapid temperature fluctuations, recommending temperature-sensitive crops such as orange or watermelon during favorable periods. Rainfall exhibits distinct seasonal patterns that impact crop recommendations across regions. Crops like jute and rice, which require high water content, are recommended under high rainfall conditions. pH values assist the model in filtering crops sensitive to soil acidity, such as pulses or legumes, which prefer near-neutral pH levels.

In the Crop Yield Prediction (CYP) dataset, variables such as Season, Crop Area, Crop Year, State, Production, and District are analyzed by ARIMA and MSGRU. The ARIMA model utilizes Crop Year and Production for forecasting time-series yield trends. Yield prediction is more effective in regions where historical patterns are stable, indicating the method's ability to learn regional productivity trends. Crop Area and Season are captured by the MSGRU model, particularly through long-term and seasonal GRU layers. While larger crop areas generally correspond to higher yield values, the method identifies diminishing returns in certain states, highlighting the impact of additional factors. Seasonality in the dataset significantly influenced the predicted yields for season-bound crops, such as Kharif rice and Rabi wheat.

Comparative Analysis

The performance of the developed ARIMA–MSGRU method is compared with existing algorithms such as HMFO-ML (Gopi and Karthikeyan, 2023) and RFOERNN-CRYP (Gopi and Karthikeyan, 2024) in Tables 7 and 8 for the crop recommendation and yield prediction processes using the CRD and CYP datasets, respectively. In Table 7, a comparison is conducted for the crop recommendation process using various evaluation metrics. In Table 8, the comparison is made for the crop yield prediction process using error metrics such as R^2, RMSE, and MAE. The novelty of the developed approach lies in the integration of ARIMA for efficient yield prediction with the MSGRU network, which effectively captures diverse temporal dependencies, including short-term fluctuations, seasonal patterns, and long-term trends. Unlike traditional GRU or LSTM architectures, the multiscale structure significantly enhances the model's ability to learn from heterogeneous agricultural data. This hybrid algorithm improves prediction accuracy and reduces error rates across multiple performance metrics.

Table 7: Comparative analysis for the Crop Recommendation process

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)
HMFO-ML	99.67	96.43	96.39	96.40	NA
RFOERNN-CRYP	98.45	98.51	98.45	98.46	99.93
Proposed ARIMA - MSGRU	99.73	99.46	99.21	99.33	98.82

Table 8: Comparative analysis of Crop Yield Prediction process

Methods	R2	RMSE	MAE
HMFO-ML	0.9882	NA	NA
RFOERNN-CRYP	0.9988	0.8377	0.2989
Proposed ARIMA - MSGRU	0.8542	0.1568	0.2582

The proposed ARIMA–MSGRU method achieved the highest accuracy of 99.73% and a lower RMSE of 1.568 compared to existing algorithms. In the WTDCNN model (Subramaniam and Marimuthu, 2024), crop production data were used for the crop yield prediction process, as evaluated in Tables 9 and 10. For a fair comparison, the proposed ARIMA–MSGRU method was also simulated using the same crop production data employed in WTDCNN, and the corresponding results are reported in Tables 9 and 10.

Table 9: Comparative analysis of Crop recommendation process with WTDCNN

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
WTDCNN	98.96	98.67	99.03	98.87
Proposed ARIMA - MSGRU	99.27	98.84	98.41	98.62

In Table 9, crop recommendation capabilities of various model is compared using different metrics. In Table 10, the crop yield prediction process is compared based on error metrics such as MSE and RMSE. The proposed ARIMA–MSGRU method achieves the highest accuracy of 99.27% and a lower RMSE of 1.624 compared to the WTDCNN model (Subramaniam and Marimuthu, 2024).

Table 10: Comparative analysis of Crop yield prediction process with WTDCNN

Methods	MSE	RMSE
WTDCNN	0.034	0.219
Proposed ARIMA - MSGRU	0.0264	0.1624

Generalization Ability

The proposed ARIMA–MSGRU method demonstrates strong generalization ability by efficiently handling heterogeneous agricultural datasets with varying temporal patterns. By combining ARIMA for modeling non-stationary trends and MSGRU for learning multi-scale temporal dependencies, the method adapts to different crop types and climatic conditions. This architecture avoids overfitting through its structured layering, ensuring consistent performance across different regions and datasets. It outperforms traditional methods by maintaining high accuracy and lower error rates even when trained on imbalanced or noisy data. The use of normalization and label encoding further supports adaptability to new datasets. Thus, the method is scalable and transferable to broader agricultural applications across geographies.

Conclusion

Choosing the appropriate crop to maximize yield is a crucial factor in enhancing real-time farming outcomes. This manuscript develops ARIMA and MSGRU models for effective yield prediction and crop recommendation. The study uses Crop Recommendation and Crop Yield Prediction datasets. Initially, data are converted into numerical values and normalized within a uniform range using label encoding and min-max normalization techniques, respectively. The ARIMA method is employed for crop yield prediction, followed by the MSGRU model to recommend suitable crops. The MSGRU model incorporates three GRU layers to extract deep features such as short-term and long-term dependencies, ensuring an effective crop recommendation process. The novelty of the developed approach lies in integrating ARIMA for accurate yield prediction with a multiscale MSGRU network, which captures temporal dependencies, short-term fluctuations, seasonal patterns, and long-term trends. Unlike traditional GRU or LSTM architectures, the multiscale structure significantly improves the model's capability of learning from heterogeneous agricultural data. This hybrid algorithm enhances the prediction accuracy and reduces the error rates across multiple performance metrics. As demonstrated by the experimental results, ARIMA–MSGRU achieves the best values compared to traditional ML and DL algorithms, attaining the highest accuracy of 99.73% and the lowest RMSE of 1.568, outperforming existing approaches.

Future Work

As a future extension, more advanced DL-algorithms like transformers will be explored to further improve temporal pattern recognition in agricultural data. Additionally, integrating satellite imagery and real-time IoT sensor data can enhance the robustness and precision of predictions.

Author Contributions

Gurupraksh Chirathahalli Dyamanna: Conceptualization; Validation; Software; Investigation; Resources; Writing – review and editing; Supervision; Project administration

Vani Vijay Kumar Ballapuram: Conceptualization; Methodology; Validation; Formal analysis; Data curation; Writing – original draft preparation; Visualization; Funding acquisition

Conflicts of Interest

The authors declare no conflict of interest.

Funding Information

This research received no external funding.

References

Abdel-salam, M., Kumar, N., & Mahajan, S. (2024). A proposed framework for crop yield prediction using hybrid feature selection approach and optimized machine learning. *Neural Computing and Applications*, *36*(33), 20723–20750. https://doi.org/10.1007/s00521-024-10226-x

Ahmed, S. (2023). A Software Framework for Predicting the Maize Yield Using Modified Multi-Layer Perceptron. *Sustainability*, *15*(4), 3017. https://doi.org/10.3390/su15043017

Bhimavarapu, U., Battineni, G., & Chintalapudi, N. (2023). Improved Optimization Algorithm in LSTM to Predict Crop Yield. *Computers*, *12*(1), 10. https://doi.org/10.3390/computers12010010

Chang, C.-H., Lin, J., Chang, J.-W., Huang, Y.-S., Lai, M.-H., & Chang, Y.-J. (2024). Hybrid Deep Neural Networks with Multi-Tasking for Rice Yield Prediction Using Remote Sensing Data. *Agriculture*, *14*(4), 513. https://doi.org/10.3390/agriculture14040513

Di, Y., Gao, M., Feng, F., Li, Q., & Zhang, H. (2022). A New Framework for Winter Wheat Yield Prediction Integrating Deep Learning and Bayesian Optimization. *Agronomy*, *12*(12), 3194. https://doi.org/10.3390/agronomy12123194

Elbasi, E., Zaki, C., Topcu, A. E., Abdelbaki, W., Zreikat, A. I., Cina, E., Shdefat, A., & Saker, L. (2023). Crop Prediction Model Using Machine Learning Algorithms. *Applied Sciences*, *13*(16), 9288. https://doi.org/10.3390/app13169288

DOI: 10.3844/jcssp.2025.2229.2237

Gopi, P. S. S., & Karthikeyan, M. (2024). Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model. *Multimedia Tools and Applications*, *83*(5), 13159–13179. https://doi.org/10.1007/s11042-023-16113-2

Gopi, S. R., & Karthikeyan, M. (2023). Effectiveness of Crop Recommendation and Yield Prediction using Hybrid Moth Flame Optimization with Machine Learning. *Engineering, Technology & Applied Science Research*, *13*(4), 11360–11365. https://doi.org/10.48084/etasr.6092

Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., Ray, S., & Mohammed, H. S. (2022). Machine Learning- and Feature Selection-Enabled Framework for Accurate Crop Yield Prediction. *Journal of Food Quality*, *2022*, 1–7. https://doi.org/10.1155/2022/6293985

Hasan, M., Marjan, M. A., Uddin, M. P., Afjal, M. I., Kardy, S., Ma, S., & Nam, Y. (2023). Ensemble Machine Learning-Based Recommendation System for Effective Prediction of Suitable Agricultural Crop Cultivation. *Frontiers in Plant Science*, *14*, 1–18. https://doi.org/10.3389/fpls.2023.1234555

Kiruthika, S., & Karthika, D. (2023). IOT-BASED professional crop recommendation system using a weight-based long-term memory approach. *Measurement: Sensors*, *27*, 100722. https://doi.org/10.1016/j.measen.2023.100722

Nagesh, O. S., Budaraju, R. R., Kulkarni, S. S., Vinay, M., Ajibade, S.-S. M., Chopra, M., Jawarneh, M., & Kaliyaperumal, K. (2024). Boosting enabled efficient machine learning technique for accurate prediction of crop yield towards precision agriculture. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00254-x

Nti, I. K., Zaman, A., Nyarko-Boateng, O., Adekoya, A. F., & Keyeremeh, F. (2023). A Predictive Analytics Model for Crop Suitability and Productivity with Tree-Based Ensemble learning. *Decision Analytics Journal*, *8*, 100311. https://doi.org/10.1016/j.dajour.2023.100311

Oikonomidis, A., Catal, C., & Kassahun, A. (2022). Hybrid Deep Learning-based Models for Crop Yield Prediction. *Applied Artificial Intelligence*, *36*(1). https://doi.org/10.1080/08839514.2022.2031823

Reyana, A., Kautish, S., Karthik, P. M. S., Al-Baltah, I. A., Jasser, M. B., & Mohamed, A. W. (2023). Accelerating Crop Yield: Multisensor Data Fusion and Machine Learning for Agriculture Text Classification. *IEEE Access*, *11*, 20795–20805. https://doi.org/10.1109/access.2023.3249205

Senapaty, M. K., Ray, A., & Padhy, N. (2024). A Decision Support System for Crop Recommendation Using Machine Learning Classification Algorithms. *Agriculture*, *14*(8), 1256. https://doi.org/10.3390/agriculture14081256

Shams, M. Y., Gamel, S. A., & Talaat, F. M. (2024). Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making. *Neural Computing and Applications*, *36*(11), 5695–5714. https://doi.org/10.1007/s00521-023-09391-2

Subramaniam, L. K., & Marimuthu, R. (2024). Crop yield prediction using effective deep learning and dimensionality reduction approaches for Indian regional crops. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *8*, 100611. https://doi.org/10.1016/j.prime.2024.100611

Thorat, T., Patle, B. K., & Kashyap, S. K. (2023). Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming. *Smart Agricultural Technology*, *3*, 100114. https://doi.org/10.1016/j.atech.2022.100114

Zhang, Z., Olk, D. C., & Linquist, B. A. (2025). Introduction of a Fallow Year to Continuous Rice Systems Enhances Crop Soil Nitrogen Uptake. *European Journal of Soil Science*, *76*(1). https://doi.org/10.1111/ejss.70046