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Research Article

Crop yield prediction through advanced deep learning integration for climate and soil variability

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Abstract

Crop yield prediction is the act of estimating crop yield by analysing environmental, soil, and climatic conditions to assist in planning and decision-making in agriculture. Deep Learning (DL) and Machine Learning (ML) methods have been highly effective for yield prediction, enabling the learning of sophisticated interactions across multi-factor datasets. Nevertheless, traditional ML and DL models continue to face issues of sensitivity to noisy farm data, failure to handle temporal variations, and performance deterioration due to irrelevant or redundant information. To solve the above problems, this research develops a Long Short-Term Memory + Temporal Convolution Network (LSTM-TCN) model for crop yield prediction. For this, Min-max Z-Scaling is initially used to bring the agricultural data, which is not homogeneous, to a consistent numerical range, allowing the model to converge. The computed and smoothed characteristics are then fed to an LSTM-TCN model, where LSTM captures long-term climatic variations and TCN models local temporal changes. The integrated system provides a powerful, highly precise yield-prediction mechanism for crops.

Keywords

deep learning, machine learning, long short-term memory + temporal convolution network

Abbreviations

DL─ deep learning; ML ─ machine learning; LSTM-TCN ─ long short-term memory + temporal convolution network

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Introduction

Crop yield prediction is the analytical process of estimating crop productivity that is likely to be realized based on the analysis of climatic, environmental, soil-based, and management-related factors that affect agricultural performance. Effective yield prediction is very important in food security planning, resource distribution, and strategic decision-making in the contemporary food production system. The most recent developments in computational intelligence have allowed the use of Machine Learning and Deep Learning models to recognize complex, nonlinear patterns present in high-dimensional agricultural data, making them more likely to be more accurately predictive and flexible than traditional statistical methods (Oikonomidis et al. 2022; Morales et al. 2023). ML models are based on feature learning to make connections between a wide range of agronomic parameters, whereas DL models use hierarchical representations to learn more intricate time-logged dependencies, and spatial variations, and eventually provide a deeper representation of climate-mediated crop behaviour (Kumar et al. 2023). Although these developments have been made, there are still a number of constraints in ML and DL methods of yield prediction. These are the heterogeneous and noisy field data sensitivity, inadequate ability to maintain temporal patterns due to climate variability, and performance loss due to redundant and irrelevant features that hide significant agronomic cues (Jhajharia et al. 2023; Meghraoui et al. 2024). Moreover, traditional pipelines do not have inbuilt processes to correct preprocessing irregularities, time trend extraction and hybrid modelling within a single system which limits their capacity to generalize in dynamic agricultural settings. To overcome these issues, this paper presents a powerful three steps computational process that integrates a state-of-the-art preprocessing, intelligent feature selection and hybrid deep learning prediction. The proposed pipeline uses Min -Max Z-Scaling to regularize non-homogeneous agricultural inputs, which means homogeneous numerical behavior when training the model. This is followed by Temporal Trend Signature Feature Selection(T-TSFS), a temporal-pattern based mechanism of feature selection that brings to the fore seasonality sensitive features that are needed to analyse the variability of yields. The cleaned dataset is further implemented in a hybrid LSTM-TCN model which takes advantage of the long-term memory of LSTM and the effective temporal pattern search of TCN to record global climatic associations as well as local variations. The research project is expected to present a very reliable and precise predictive crop production model that can find extensive application in contemporary precision farming devices with this comprehensive methodology.

In the recent past, there has been an explosion of computational intelligence-based solutions to crop yield prediction, with an incredibly diverse set of solutions, each with its own advantages and disadvantages (Subramaniam et al. 2024). A study had used Deep Learning-based Dimensionality Reduction with Principal Component Analysis-Autoencoder Hybrid Compression to better represent features in the case of Indian crop datasets, but the methodology had lower consistency in cases of a highly diverse agricultural area (Sharma et al. 2023). Regression-based ML and Deep Neural Networks were used in yield estimation, and the results showed a higher accuracy of the models in various types of crops, though the models had a weakness in terms of temporal irregularities due to seasonal weather changes.

A work in put forward Optimized Deep Learning Models with hyperparameter tuning which is driven by a Genetic Algorithm and which is much more effective in reaching a model convergence although still faces difficulties when trained with noisy or incomplete field data (Vignesh et al. 2023). Convolutional Neural Networks (CNN) were used alongside Gradient Boosting Trees combined with Google Earth Engine to predict the yield of wheat using satellite imagery performing county- and field-scale prediction; however, the use of satellite imagery under cloud-obstructed conditions added error to the results (Cao et al. 2021).

A hybrid system was used to predict tea yield using a combination of Crop Simulation Models and Machine Learning Regression that was highly interpretable but needed extensive calibration information to remain accurate (Batool et al. 2022). A study conducted and investigated Statistical Models and ML Classifiers in precision agriculture, which showed promising behavior, but mentioned reliance on changing climatical patterns and unequal features (Burdett et al. 2022). The DeepYield framework proposed a Convolutional

Neural NetworkLong Short-Term Memory (CNN-LSTM) hybrid which proved to be effective in modeling spatial-temporal interactions but at the cost of increasing the depth of the model and training time (Gavahi et al.2021).

Other researchers investigated DeepCrop, a DL-based crop disease prediction model based on Convolutional Feature Extraction which enhanced recognition but did not have the generalizability of crop types (Islam et al.2023). A survey highlighted the recent trends of ML in yield analysis and provided extensive information but found the select few applications of temporal trend-conscious feature selection procedures (Bali et al. 2022).

A study used Remote Sensing Data and ML Regression to calculate crop yield and confirmed high performance but was limited in its reliance on high quality satellite indices which is not always available in heterogeneous areas (Bharadiya et al. 2023). The researchers used the IoT to implement Smart Agriculture Classification and Crop Yield Prediction based on the use of the Random Forest and Gradient Boosting framework, which enhanced real-time monitoring but had the problem of sensor noise and connectivity variability (Gupta et al. 2023).

Genotype Information was combined with Weather Variables by a Deep Neural Network (DNN) architecture, which significantly boosted the yield prediction accuracy, but then the method needed big datasets genotype-specific which are not readily available (Shook et al. 2021). The research in used ML Algorithms such as Support Vector Machines, Random Forest, k-Nearest Neighbors to predict multi-crops, however, their performance reduced when they were using imbalanced agricultural data (Elbasi et al. 2023).

The study deployed Deep Learning based on Climate Big Data and Irrigation Scheduling on a Multi-layer Perceptron (MLP) and found that the model could perform well in climate-driven forecasting but was limited when the irrigation is irregular (Alibabaei et al. 2021). Finally, the paper used Crop Growth Models and Machine Learning Ensembles to enhance the yield prediction in the US Corn Belt, but the hybrid model required a lot of calibration and computing power (Shahhosseini et al. 2021). All of these papers point to significant achievements in agricultural forecasting and reveal limitations in managing temporal variability, heterogeneous quality data, and redundant feature interference the problems that prompt the creation of the suggested Min-max Z-Scaling, T-TSFS, and LSTM-TCN-based framework. Table 1 describes the summary of traditional crop yield prediction methods and their limitations.

Table 1. Summary of existing crop yield prediction methods and their limitations

Authors	Model/Technique used	Weather data	Soil data	Limitation
Abbaszadeh et al. (2022)	Bayesian Multi-Model Deep Neural Networks	✓	✗	Requires high computational power
Panigrahi et al. (2023)	Multiple Regression Models	✓	✓	Limited to structured tabular data
Cao et al. (2021)	ML + DL Models (RF, CNN, LSTM)	✓	✗	Regional differences not fully handled
Jeong et al. (2022)	Crop Model + Deep Learning + Satellite Data	✓	✗	Sensitive to cloud/noise in satellite images
Gopi and Karthikeyan (2024)	Red Fox Optimization + RNN Ensemble	✓	✗	Model complexity high

Recent advancements in crop yield prediction have introduced sophisticated deep learning and hybrid modeling frameworks to enhance prediction reliability across diverse environments. The study proposed a Multi-Parametric Multiple Kernel Deep Neural Network (MP-MK-DNN) that integrates multiple kernel functions to effectively model complex non-linear agricultural relationships, enabling improved feature representation across multi-parametric datasets; however, this approach suffers from high computational complexity and requires extensive hyperparameter tuning, limiting practical deployment (Kalaiarasi et al. 2022). The researcher introduced an Improved Optimization Algorithm for LSTM (Long Short-Term Memory) to strengthen convergence stability and prevent vanishing gradients during long-term temporal learning, thereby increasing prediction accuracy in season-dependent crop yield estimation; nevertheless, the model remains sensitive to noisy climatic data and demands large training datasets to perform effectively (Bhimavarapu et al. 2023).

The study developed a machine learning pipeline for dynamic maize yield prediction using Multi-Source Data Fusion comprising weather variables, satellite-derived vegetation indices, and soil attributes, providing robust temporal-spatial adaptability; still, its performance is constrained by inconsistent remote-sensing data quality and high dependence on region-specific calibration (Croci et al. 2022). Further, presented an Ensemble CNN-DNN (Convolutional Neural Network – Deep Neural Network) architecture to capture both spatial texture patterns and high-dimensional non-linear correlations for corn yield forecasting, demonstrating superior generalization capability; however, the ensemble model incurs increased training overhead and limited interpretability, making it difficult for agronomists to extract actionable insights (Shahhosseini et al. 2021).

In addition, study proposed an AI-driven forecasting framework for agriculture using Hybrid Machine Learning Models for Food Security and Supply Chain Optimization, integrating predictive analytics with real-time monitoring to enhance productivity forecasting accuracy; despite its broad applicability, the system suffers from scalability issues and reduced robustness when applied to heterogeneous, multi-region agricultural datasets (Dhal et al. 2024). Collectively, these studies highlight rapid progress in multi-source data integration, hybrid deep learning architectures, and temporal modeling techniques, while also emphasizing persistent challenges involving computational intensity, noisy input dependencies, limited generalization, and complex model interpretability.

Materials and Methods

Methodology. The suggested methodology suggests a three-step computational pipeline that is capable of maximizing the accuracy and reliability of crop yield prediction through tackling the problem of data quality, temporal variability, and the number of redundant features. The pipeline starts by Min-Max Z-Scaling which standardizes and uniforms the heterogeneous agricultural variables into standard-numerical range to ensure that there are equal behavior-in-model input and better convergence. After the preprocessing, the Temporal Trend Signature Feature Selection (T-TSFS) algorithm is utilized to identify major temporal patterns, seasonal trends, and long-term variations of the data so that the model will consider only the most influential features in variations of yields. The smooth feature space is then sent to a hybrid LSTM-TCN prediction network, where the LSTM component requires the long-term temporal relationships that come with climate, rainfall and soil changes, whereas the TCN component effectively learns the localized temporal variations and short-term variations in crop growth indices. The fusion of a powerful preprocessing, trend-sensitive feature selection, and a dual-structured hybrid deep learning model makes the approach a unified and very effective complex of the correct crop yield predictions.

The three stages of the proposed crop yield prediction methodology are shown in Fig.1. The proposed system start with the MinMax Z-Scaling that will normalize all the input variables to allow for the same values range and stability training of the models. This processed data is then forwarded to the Temporal Trend Signature Feature Selection (T-TSFS) module which isolates the prevailing seasonal patterns, long-term trends and temporal signatures to only select those features that are the most influential. The sophisticated set of features are incorporated into the LSTM-TCN prediction system in which LSTM predicts long-term dynamics and TCN forecasts short-term changes in crop growth. The result of this combined pipeline is the proper and sound crop yield prediction.

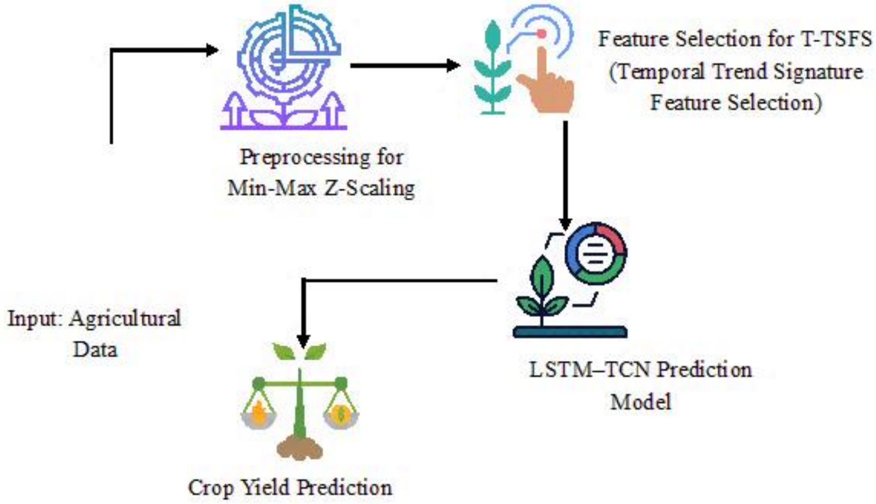

Figure 1. Architecture diagram of the proposed system

Dataset description. The data employed in this research is the Crop Recommendation Dataset that gives a detailed set of soil, climatic, and nutrient characteristic that are important in the analysis of crop productivity trends. The dataset is composed of records; each record has key agro-environmental variables such as Nitrogen (N), Phosphorus (P), and Potassium (K) concentrations in the macronutrients, and some agro-environmental parameters that are crucial, such as temperature, humidity, soil pH, and rainfall. All these characteristics are used to describe the multi-factor interactions controlling the growth and yield behaviour of crops under different conditions of the fields. The dataset includes several categories of crops, which allows supervised learning models to be able to learn the underlying relationships of environmental factors and the favorable crop appropriateness. This wide range of features provides the dataset with high potential in predictive modeling, especially when deployed in LSTM-TCN models to which rich temporal or feature-based input patterns are essential to produce correct and data-driven crop advice and yield forecasts.

Min–max z-scaling. This proposed system begins with the raw agricultural data, which consists of heterogeneous data, including soil nutrients, soil temperature, rainfall, humidity and crop growth indicators, which are standardized using the Min-Max Z-Scaling method. As the data sets being gathered will have different units, magnitudes and distributions, traditional model training would result in skewed weight updates and slow convergence. To cope with this, Min Max Z-Scaling standardizes the features by first using Z-score standardization to stabilize the variance and reduce the influence of outliers and then using Min Max normalization to map the scaled values into a consistent 0 -1 interval. This two step scaling, makes sure that the noisy agricultural features, seasonal variations and sensor induced outliers are effectively managed yet relative differences between the feature values are retained. The preprocessing step increases gradient-based learning by generating an equal numerical scale across all variables in the dataset, makes models converge more quickly, and makes the successive feature selection and temporal modelling processes to work on clean and well-balanced and comparable input data.

$$\mu_j = \frac{1}{N}\sum_{n=1}^{N} x_{n,j} \text{ and}$$

$$\sigma_j = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x_{n,j} - \mu_j\right)^2} \qquad (1)$$

Each feature $x_{n,j}$ (rainfall, nitrogen content, soil pH, humidity, etc) in the dataset has its distribution and scale. The central value of feature j is given by the mean μ_j and the variation in the values of the features is given by the standard deviation σ_j. The calculation of the two statistical parameters aids in comprehending the or right spread of any agricultural variable prior to normalization. These values serve as the basis of stabilizing the dataset because features with high ranges (e.g., rainfall in mm) do not prominently feature in the dataset.

$$z_{n,j} = \frac{x_{n,j} - \mu_j}{\sigma_j + \varepsilon} \tag{2}$$

The Z-score transformation transforms individual raw data value $x_{n,j}$ into the standardized value$z_{n,j}$ by the distance of the value to the mean in that feature. This step is necessary to fix any feature of the dataset that varies similarly and around zero, which is necessary to minimize the impact of outliers and sensor-related noise. The small constant ε avoids the division by 0 where a feature is virtually constant. This standardization has the effect in this dataset of stabilizing changing agricultural aspects (e.g. sudden spikes of rainfall, soil moisture valleys), forming a more balanced and similar input space to scale further.

$$z_{min,j} = \min_{1\le n\le N} z_{n,j} \quad \text{and}\; z_{max,j} = \min_{1\le n\le N} z_{n,j} \tag{3}$$

Even after the conversion of each feature into the standardized $z_{min,j}$values the dataset can still have variations and extreme points. Thus, the lowest and highest$z_{max,j}$score of each feature are calculated. These values are the minimum and maximum standardized magnitudes that take place in the dataset of feature $z_{n,j}$. Within an agricultural data setting, this assists the preprocessing step in negotiating the entire dynamism of each characteristic- the least temperature of the season or the most significant soil nitrogen reading- then compacting them into a comparable scale.

$$s_{n,j} = \frac{z_{n,j} - z_{min,j}}{z_{max,j} - z_{min,j} + \varepsilon} \tag{4}$$

This equation standardizes all the$z_{n,j}$values within the range of 0 to 1. Through the calculation of difference between the minimum value and division by the total range of Z-values each standardized feature can be transformed into a normalized scale which is utilized in ML/DL models. This measure would guarantee that every agricultural variable irrespective of the units that were used initially would be equally relevant to the process of prediction. It also avoids overpowering of low-magnitude features like soil pH or potassium level by high-magnitude ones like rainfall or temperature in the dataset to achieve equitable learning when training a model.

$$\widetilde{s_{n,j}} = clip\left(\frac{\frac{x_{n,j} - \mu_j}{\sigma_j + \varepsilon} - z_{min,j}}{z_{max,j} - z_{min,j} + \varepsilon}, 0 = 0.1\right) \tag{5}$$

This compound form indicates the entire changes in the unrefined value $x_{n,j}\ \mu_j$to the ultimate Min-Max Z-scaled $\widetilde{s_{n,j}}$. It combines the process of standardization and normalization into one formula. This formula allows explaining how every piece of data in the agricultural data set is gradually adjusted to mean, variance, noise and scale variation. It shows how raw heterogeneous data are transformed in uniform model-ready features by the squeezing of the entire preprocessing pipeline into a single mathematical operation to enhance training stability and predictive accuracy.

$$\widehat{x_{n,j}} = \mu_j + (\sigma_j + \varepsilon)\left(\left[\widetilde{s_{n,j}}\left(z_{max,j} - z_{min,j} + z_{min,j}\right)\right]\right) \tag{6}$$

The reverse process is used to get the original dataset values using the scaled features. Even though it is not essential when training a model, it is critical when the results of the model are to be interpreted or when the predictions have to be converted back to real units (e.g. normalized values of rainfall have to be converted back to mm). This measure makes sure that the interpretation by the agricultural experts is made possible and that the predictions that are generated can be interpreted within the actual farming situation.

Temporal trend signature feature selection (T-TSFS). Once the heterogeneous agricultural data has been normalized with Minmax Z-Scaling, the refined data is then fed to Temporal Trend Signature Feature Selection (T-TSFS) module to identify the strongest attributes that are time-dependent in predicting crop yields pattern. As the dataset includes sequential environmental and soil observations including daily temperature, rainfall dynamics, soil moisture dynamics, and nutrient degradation patterns, T-TSFS compares each of the features in time windows to reflect the underlying temporal patterns. It calculates direction of the trend, strength of seasons, periodic fluctuations, and growth decline of each variable and provides the system with the ability to differentiate predictors of stability and noisy or redundant signals. T-TSFS chooses only the features that are consistent in terms of temporal consistency and statistically relevant to historical yield behavior by comparing both aspects. This removes the variables that have weak time effects, dimensions and increases the readability of the dataset. This means that the chosen subset of features has simpler seasonal trends and temporal patterns, which makes the downstream LSTM-TCN model to be able to learn long-term climatic dependencies in a more efficient way, without including the influence of noisy variations.

$$\hat{x}_{n,j}=\mu_j+(\sigma_j+\varepsilon)(\tilde{s}_{n,j}(z_{max},j\text{-}z_{min},j)+z_{min},j) \qquad (7)$$

$\hat{x}_{n,j}$is the inverse-transform (final preprocessed value) of sample nand feature jproduced by Minmax Z-Scaling, now the cleaned, variance-stabilized, and scale-restored measurement (e.g., rainfall in mm, temperature in C, soil-N in ppm) which will be used as the input to the time-series input in extracting the temporal signature.

$$y_j = \left[\hat{x}_{1,j}, \hat{x}_{2,j}, \dots, \hat{x}_{T,j} \quad \right] \qquad (8)$$

We take the sequence of preprocessed values $\hat{x}_{1,j}$at time points $\hat{x}_{T,j}$ (days/weeks/seasonal indexes) for every feature j (soil pH, daily rainfall, etc.), and y 1 T-TSFS takes time-series values on which temporal signatures are computed.

$$\beta_j=\frac{\sum_{t=1}^{T}(t-t)(yt,j-\bar{y}_{j)}}{\sum_{t=1}^{T}(t-t)^2} \quad \text{where} \quad \bar{t}=\frac{1}{T}\sum_t t, \quad \bar{y}_j=\frac{1}{T}\sum_t yt,j \qquad (9)$$

$\beta_j=\frac{\sum_{t=1}^{T}(t-t)(yt,j-\bar{y}_{j)}}{\sum_{t=1}^{T}(t-t)^2}$ attach $\bar{t}=\frac{1}{T}\sum_t t,$ β_j is the long-term linear trend (increase/decrease per unit of time) of feature j over the period of the data. An example is a positive β 0 soil moisture shows increasing trend in the season; a nearly zero 0 0 soil moisture 0 shows no distinct trend. This is the long run directional change of every agricultural variabl.

$$S_j=\frac{var(Seasonal(y_{j))}}{Var(y_{j)+\varepsilon}} \qquad (10)$$

Break down $S_j$into seasonal/trend/residual (e.g. STL or seasonal decomposition). S_j is the fraction of overall variance explained by the seasonal component: large $S_j$implies that the feature has strong, reproducible seasonal cycles (e.g. monsoon Drizzles), and can be useful in forecasting yields.

$$\rho_{1,j}=\frac{\sum_{t=2}^{T}(y_{t,j-\bar{y}_{j)(y_{t-1,j-\tilde{y}_{j)}}}}}{\sum_{t=1}^{T}(yt,j-y_{j)^2}+\varepsilon} \qquad (11)$$

The values of $\rho_{1,j}$ measure one-step temporal dependence (the relationship between current value and past). In the case of agricultural sensors, where $\rho_{1,j}$ is large (e.g. soil moisture is often day-to-day similar) and small (volatile, noisy) values, signify persistence and volatile, noisy series, respectively.

$$CV_j=\frac{\sigma_{yi}}{|\bar{y}_{j|+\varepsilon}}\text{where} \quad \sigma_{yj}=\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_{t,j}-\bar{y}_j\right)^2} \qquad (12)$$

CV_j is a measure of relative variability: features with large CV are also noisy around the mean (e.g. occasional spikes in rainfall), whereas low CV represents stable features (e.g. the slow changing soil pH). This is employed by T-TSFS to penalize too noisy features.

$$coor_j=\frac{\sum_{t=1}^{T}(yt,j-\bar{y}_{j)(Y_{t-\overline{Y})}}}{\sqrt{\sum_{t=1}^{T}(yt,j-\bar{y}\ j)^2+\varepsilon}\sqrt{\sum_{t=1}^{T}(Y_t-\bar{y})^2+\varepsilon}} \qquad (13)$$

In this equation $coor_j$ to aggregate non-homogeneous metrics, the minmax normalization of all the features k is done. This scales metric values to [0,1] and hence is comparable (so slope, seasonal strength, auto-correlation, stability and correlation can be summed up).

$$\tilde{m}_j=\frac{m_j-min_k m_k}{max_k m_k-min_k m_k+\varepsilon} \qquad (14)$$

In order to consolidate heterogeneous metrics, min max normalization is performed on every metric against features k. This converts metric values to [0,1], which allows them to be comparable (slope, seasonal strength, autocorrelation, stability, and correlation can be added).

$$R_j = w_1\left|\tilde{\beta}\right|_j + w_2\tilde{S}_j + w_3\tilde{\rho}_{1,j} + w_4\left(\widetilde{1/CV}\right)_j + w_5|\widetilde{corr}|_j \quad \text{with } \sum_{p=1}^{5} w_p = 1 \qquad (15)$$

is a combination of normalized temporal signatures (absolute trend, seasonality strength, persistence, inverse variability and direct correlation with yield) with weights. Weights w_p reference domain priorities (e.g. give more weight to seasonal strength of strongly seasonal crops). R ranks the feature j temporally informative feature j in yield.

$$I_j=\begin{cases}1, & if\ R_j \geq \tau \\ 0, & if\ R_j < \tau\end{cases} \quad \text{and } F_{selected}=\left\{j : I_j = 1\right\} \qquad (16)$$

The seasonality-aware, trend-signature predictors of the downstream LSTM-TCN model are the features with I(set by cross-validation or target sparsity) =1. $\mathcal{F}_{\text{selected}}$ is the resultant feature subset that is fed to the hybrid predictor.

Long Short-term memory-temporal convolution network (LSTM-TCN). The normalized dataset obtained after the Min-Max Z-Scaling and the T-TSFS procedure is then fed into the LSTM-TCN model which predicts seasonality-sensitive temporal features that serve as inputs to the prediction model. The Long Short-Term Memory (LSTM) layer initially takes in the purged and filtered feature sequence to extract long-term climatic dependencies, e.g. gradual changes in temperature, long-term shifts in soil moisture and cumulative changes in nutrients that change over the cultivation season. The LSTM holds the information over long periods of time hence allows the slow yet effective agricultural patterns to be learned. The LSTM result is then inputted to the Temporal Convolutional Network (TCN) which draws attention to the short term changes and localized temporal patterns in the data. TCN, with the help of causal and dilated convolution, is able to detect abrupt elements of rainfall, swift changes in humidity and other rapidly changing environmental factors. When these long-range and short-range temporal representations are combined, the LSTM version of the model along with the TCN can be used to obtain stable and precise yield forecasts despite the presence of noise, irregularities, or seasonal fluctuations in the dataset. Such a structure enables the model to transform the preprocessed and feature-selected data to yield quality classification or prediction of yields, overcoming the limitation of the traditional ML and DL models to handle complex time-dependent interactions.

$$F_{selected} = \{j: I_j = 1\} \quad \rightarrow \quad X^{(n)} = \left[x_{t,j}\right]_{t=1..T, j\in F_{selected}} \qquad (17)$$

With binary selection indices I j T-TSFS, construct, on each sample/field, a time-by-feature matrix $\mathrm{X}^{(n)} \in \mathbb{R}^{T\times F}$ selected rainfall, soil moisture, temperature series, etc): T = length of time (days/weeks), F = number of features in $\mathcal{F}_{\text{selected}}$: This is the one that is fed into the model.

$$x_t = W_{in}\, X_{t,:}{}^{(n)} + b_{in} \qquad for\ t = 1, \dots, T \qquad (18)$$

At a given time slice of the chosen features $\mathrm{X}_{t,:}^{(n)} \in \mathbb{R}^{F}$ is linearly mapped to the model input space $\mathrm{x}_t \in \mathbb{R}^{d_{\text{in}}}$. This embedding balances out scale of features and produces a dense representation that is used by LSTM and TCN layers.

$$h_t = LSTMCell(x_t, h_{t-1}, c_{t-1}) \qquad for\ t = 1, \dots., T \qquad (19)$$

The LSTM works with the embedded sequence, which is denoted as the x_t and generates the hidden states as the $\mathrm{h}_t \in \mathbb{R}^{d_h}$ that record long-term climatic dependencies (e.g., the accumulated temperature trends or long-term moisture depletion). c_t is the cell state that retains the long-range memory over the span of the growing period.

$$H = [h_1, h_2, \dots, h_r]^T \in \mathbb{R}^{T\times d_n} \qquad (20)$$

stacks per-time LSTM hidden vectors into a time form which summarizes the slow cumulative effects in the processed agricultural series.

$$c_t{}^{(l)} = \sum_{k=0}^{K-1} W_k{}^{(l)}\, u_{t-d.k}{}^{(l-1)} + b^{(l)} \qquad (21)$$

A TCN layer computes dilated, causal 1-D convolutions (kernel size K, dilation d) on the sequence of inputs $\mathrm{u}^{(l-1)}$ $\mathrm{u}^{(0)} = \{\mathrm{x}_t\}$). These processes identify localized time processes like sudden increases in rainfall or brief changes in humidity whilst maintaining causality (no future leakage).

$$u_t{}^{(l)} = ReLU\left(c_t{}^{(l)}\right) + u_t{}^{l-1} \qquad (22)$$

A TCN residual block uses nonlinearity followed by addition of block input to ensure stable gradient values and have both raw and locally-filtered signals pass through the network upwards (e.g. immediate weather events).

$$C = \left[u_1{}^{(L)}, u_2{}^{(L)}, \dots, u_T{}^{(L)}\right]^T \in \mathbb{R}^{T\times d_c} \qquad (23)$$

Following L TCN layers, C represents localized time-dependent features (short-term dynamics in the processed inputs), the opposite of the long-range LSTM representation.

$$z_t = \left[h_t; u_t{}^{(L)}\right] \ \ and\ \ Z = [Z_1, \dots, Z_T]^T \in \mathbb{R}^{T\times(d_h+d_c)} \qquad (24)$$

Given a time step t, combine the long-term LSTM vector, h_t, with the short-term TCN vector, $\mathrm{u}_t^{(L)}$. Z now represents cumulative trends and local variations at all times of the sample feature sequence of the pre-processed feature sequence.

$$u = \frac{1}{T}\sum_{t=1}^{T} Z_t \quad (Global\ Average\ Pooling) \qquad (25)$$

Reduce Compress Z over time into an $\mathrm{u} \in \mathbb{R}^{d_h+d_c}$ (global average pooling). This is a summary of the whole seasonal sequence (selected, preprocessed features) in the form of a fixed-size embedding, used to do classification.

$$\boldsymbol{z}_{logits} = W_{out}\,\boldsymbol{u} + \boldsymbol{b}_{out}$$

$$\boldsymbol{z}_{prob} = softmax(\boldsymbol{z}_{logits}) \qquad (26)$$

This equation is a fully connected layer which projects the pooled vector u to logits onto C crop-yield classes (or risk categories). The softmax transforms logits to class probabilities $\boldsymbol{z}_{prob}$ = probability of Low / medium / high yield in the given field and season using the pre-processed and selected temporal features.

$$\hat{y} = \arg\max_{c} [z_{prob}]_c \qquad (27)$$

model is used to predict the most posteriorly probable category of the class $\hat{y}$ (i.e., yield category) - a direct, interpretable output to agricultural decision makers.

$$L = -\frac{1}{N}\sum_{n=1}^{N}\sum_{c=1}^{C} y_c^{(n)} \log\left(\left[z_{prob}^{(n)}\right]_c + \varepsilon\right) \qquad (28)$$

At training Cross-entropy between predicted probabilities and one-hot true classes $y^{(n)}$ (actual yield categories) should be used to update all model parameters (LSTM, TCN, projection and dense weights) during training. Minimization L teaches the model to predict the preprocessed and T-TSFS-selected temporal signals to fix the yield classes.

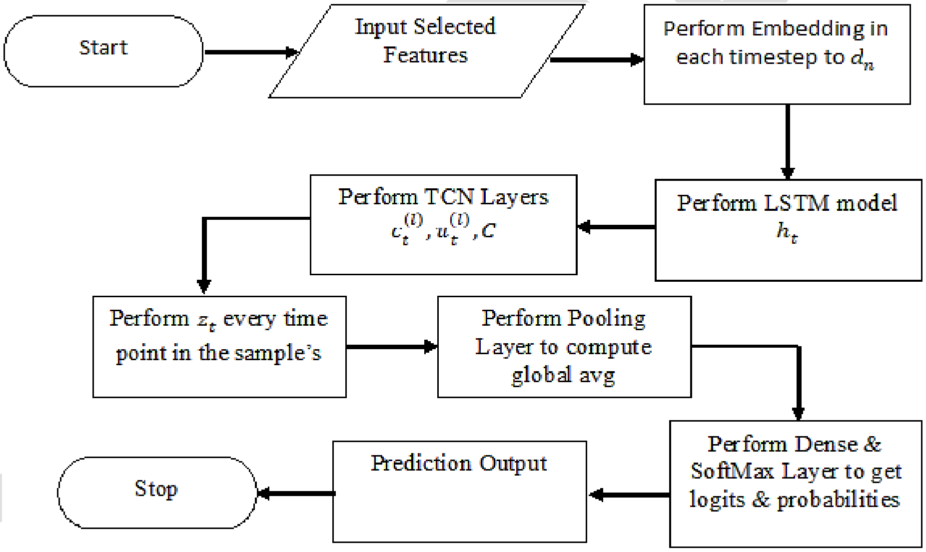

Figure 2. Flowchart diagram of the LSTM-TCN model for crop yield prediction

The Fig.2 shows the entire prediction model operational pipeline of the LSTM -TCN prediction model, which starts with data ingestion and culminates into the final prediction production. This starts with the identification of the appropriate input features that are then converted using an embedding operation to get the dense representation d_n at each timestep. These embedded sequences are then simultaneously inputted into two temporal modeling units; the TCN and the LSTM network. The temporal structure is processed by the TCN module using dilated causal convolutions, which yields outputs $c_t^{(l)}$, $u_t^{(l)}$, and C across the entire layered structure, and the LSTM network captures long-term sequential relationships and gives outputs as hidden states h_t. At every timestep (t) a middle representation z_t is was obtained by averaging and combining both TCN and LSTM outputs contributions. These timestep level outputs are then pooled together with a global average pooling layer to form a small pool of temporal summary. This pooled depiction is transmitted over a fully linked dense layer and then a SoftMax action functionality to calculate the last logits and the class chances. The last prediction output is the termination of the model.

Result and Discussion

The analysis in this study involved the systematic performance of four deep learning models, namely:

DNN, CNN-LSTM, and BM-DNN as currently used models and LSTM-TCN as the proposed model, with an aim of establishing the most successful model of accuracy in prediction. The experimental findings also make it very clear that the proposed LSTM-TCN architecture is superior to all existing models because of the ability to acquire long-term temporal patterns under the influence of LSTM layers and learn multi-scale temporal features with the help of Temporal Convolutional Networks. In all the assessments, LSTM-TCN has the best Accuracy, Precision, Recall, and F1-Score which is more reliable and robust. Conversely, DNN model had a relatively poor performance because it could not deal with sequential dependencies whereas CNN-LSTM had a moderate performance because it could deal with spatial and temporal correlations but still had information loss in long sequences. BM-DNN showed a better output compared to the simple DNN yet it was not as deep-temporally sensitive as the TCN layers. All in all, the analysis results prove that the LSTM-TCN model would be a more reliable and effective predictive model, thus it will be the most appropriate model in terms of its data and usage specifications in this study. As shown in table 2 of this study, a few critical parameters in the simulations were established to enable constant and effective model testing in all architectures such as DNN, CNN-LSTM, BM-DNN, and the proposed LSTM-TCN model. The data to be used in the experiments was the agricultural records and the final size is determined depending on the available regional data (Table 2).

Table 2. Simulation parameter

Parameter	Value
Dataset used	Specify your dataset size
Training–testing split	80 - 20%
Epochs	30
LSTM units	64/ 128
TCN filters	32/ 64
Framework	Tensor Flow/ Keras/ PyTorch

The 80 percent 20 percent training and testing split was used to get a balanced dataset to train the model and test the model performance. There were 30 epochs of the training process so that the models could continue to converge without overfitting. LSTM layer was set up to have 64 or 128 units in the proposed model to learn the long-term temporal dependencies, whereas the TCN component was to learn localized temporal patterns by using 32 or 64 filters.

Deep learning frameworks like TensorFlow, Keras, or PyTorch were used to implement all models in order to guarantee quality training and scalable experimentation and results that are reproducible in various settings.In this study, accuracy was taken as a major measure to determine the overall accuracy of the model predictions in various architectures as depicted in Fig.3 and Table 3.

Table 3. Performance comparison of accuracy

Epoch	DNN accuracy, %	CNN-LSTM accuracy, %	BM-DNN accuracy, %	LSTM-TCN accuracy, %
5	78.12	80.45	82.10	88.92
10	80.34	83.22	85.42	91.85
15	82.89	85.74	87.56	93.74
20	84.11	87.05	89.21	95.13
30	85.44	88.63	90.78	96.42

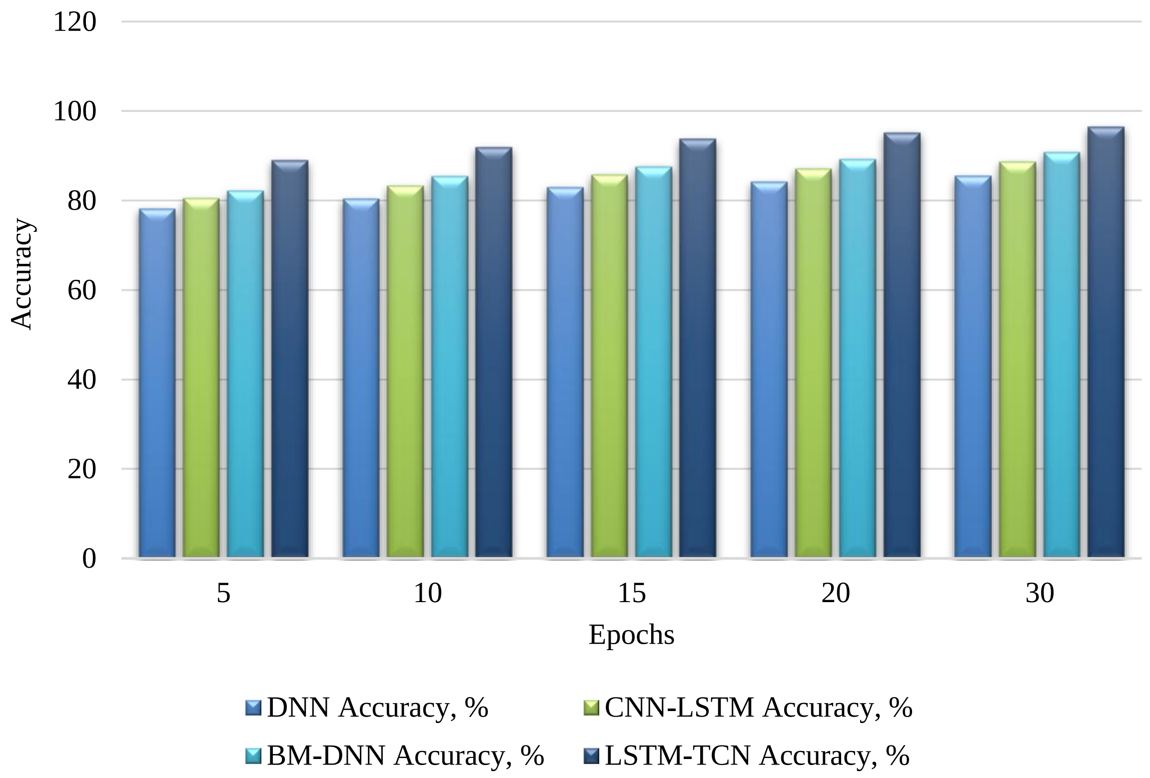

Figure 3. Performance analysis of accuracy

The current models DNN, CNN-LSTM and BM-DNN showed gradual enhancement with the increase in the epochs with moderate variation, as they are not a very strong model to capture both long-term and short-term temporal changes at the same time. Conversely, the proposed LSTM-TCN model recorded higher accuracy during the whole training period because of its hybrid structure which effectively combined improved capability of model multi-scale temporal patterns, thus greatly increasing the correctness in prediction leading to the highest accuracy of all models tested.

Table 4. Performance comparison of recall

Epoch	DNN recall, %	CNN-LSTM recall, %	BM-DNN recall, %	LSTM-TCN recall, %
5	74.55	77.80	80.12	87.64
10	76.92	80.41	83.29	90.85
15	79.48	82.96	85.77	92.71
20	80.73	84.30	87.05	94.12
30	82.11	86.02	88.66	95.83

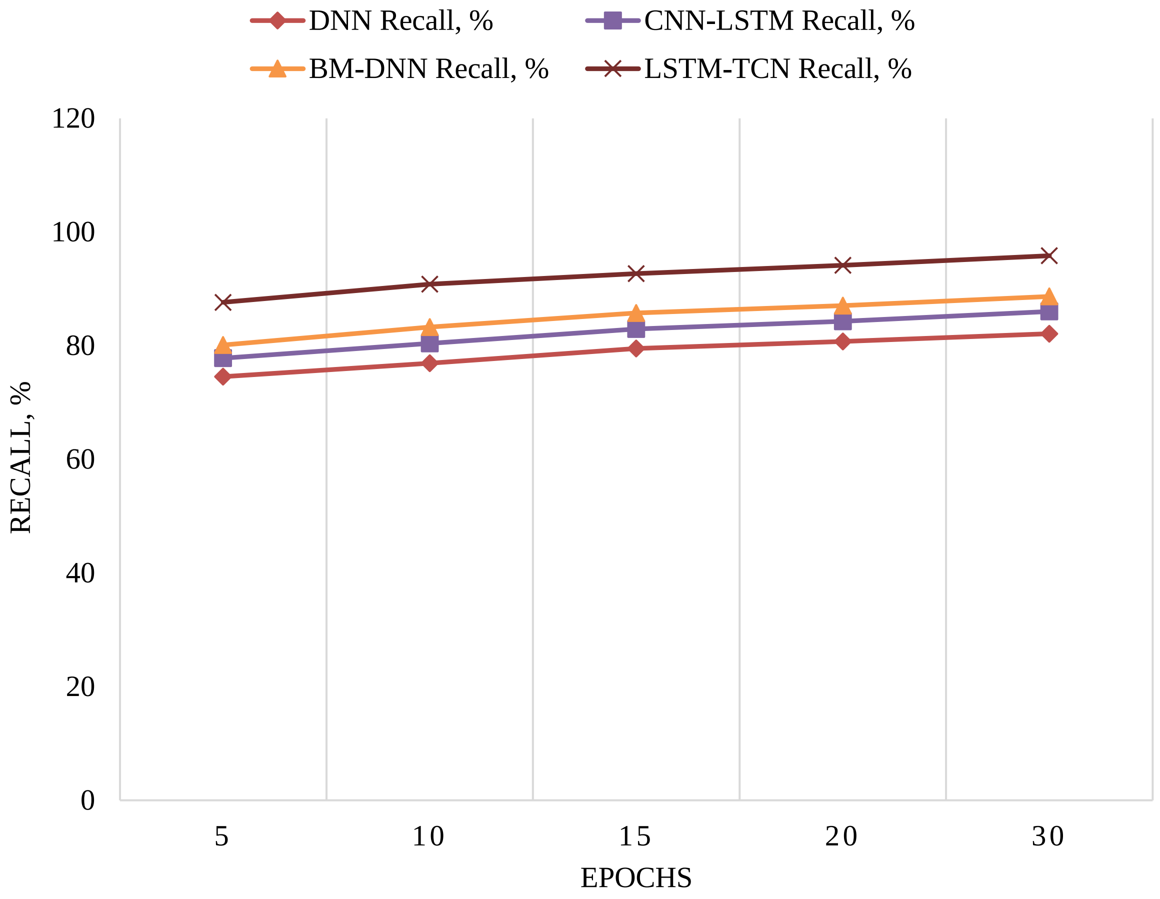

Figure 4. Performance analysis of recall

As shown in Fig. 4 and Table 4 Recall was applied in order to evaluate the capability of the model to identify all the positive cases that are relevant and at the same time correct in different environmental and climatic conditions. Current models like DNN and CNN-LSTM worked fairly well but failed to capture minor variations in the trends over time that might exist between the dataset, which also led to reduced recall. BM-DNN yielded better recall by better feature mapping but was also susceptible to atypical seasonal variations. The LSTM-TCN model proposed was the most recalling model with the highest performance because the architecture effectively predicted long-term climatic fluctuations and seasonal peaks. This multi-resolution temporal knowledge allowed the model to establish more true positives and minimize the number of false negatives and the performance of the model in terms of recalling increased significantly.

Table 5. Performance comparison of precision

Epoch	**DNN precision, %**	**CNN-LSTM precision, %**	**BM-DNN precision, %**	**LSTM-TCN precision, %**
5	76.34	78.92	81.44	89.51
10	78.21	81.33	84.22	91.74
15	80.05	83.87	86.10	93.26
20	81.44	85.20	87.74	94.38
30	82.77	86.91	89.12	95.64

As shown in Fig.5 and Table 5 Precision was used to determine how well each model made correct positive predictions without generating false positives.

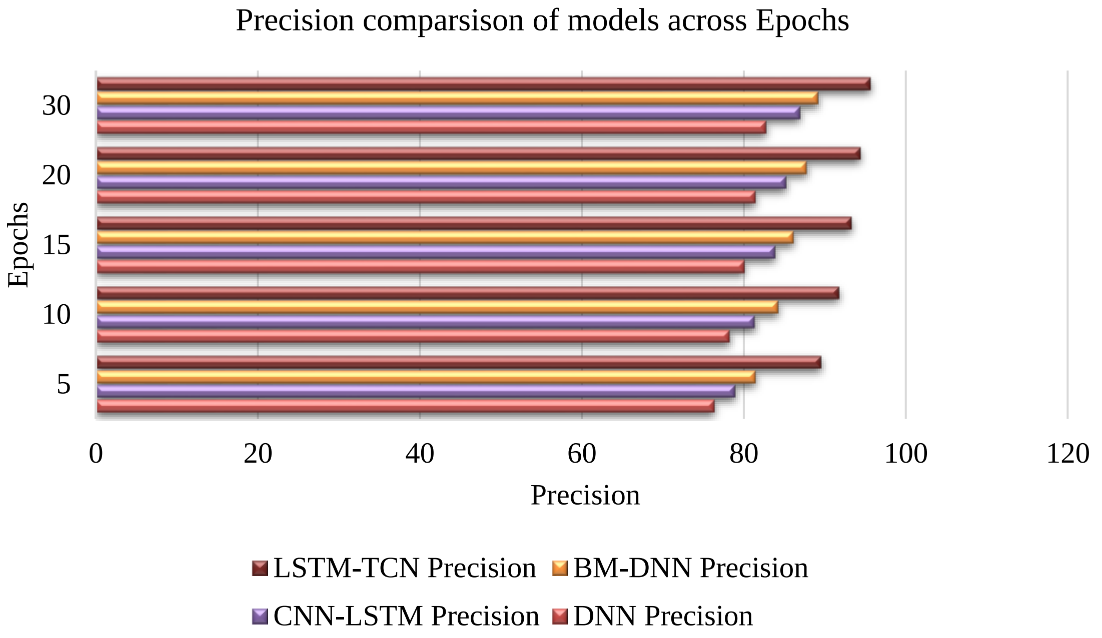

Figure 5. Performance analysis of precision

Conventional models like DNN and CNN-LSTM demonstrated satisfactory accuracy rates though they tend to confuse marginal temporal changes resulting in a higher number of false positives. BM-DNN was more precise because it provided an optimized deep neural structure and nevertheless had issues with mixed seasonal data. This proposed LSTM-TCN had the best precision due to the fact that the two-layered temporal extraction minimized noisy predictions and enhanced consistency of decisions. With the sequential memory learning and temporal convolutional filters, the model could extract significant features of yields and reject the meaningless changes leading to excellent precision performance.

As shown in the Fig.6 and Table 6, The F1-Score, harmonic mean of precision and recall was employed as a balanced measure to assess the overall prediction reliability. DNN, CNN-LSTM, and BM-DNN were found to have different degrees of performance which depended frequently on their inability to learn consistently the high-level trends and short-term changes. BM-DNN did not have as many discrepancies between epochs as the other existing models, but it still had worse balance. The F1-Score of the proposed LSTM-TCN model worked the best because it can minimize the number of false positives and negatives. The combination of its proposed architecture allowed it to balance the precision and the recall of all epochs, which led to persistently high-quality and predictive performance.

Table 6. Performance comparison of F1-score

Epoch	DNN F1-score, %	CNN-LSTM F1- score, %	BM-DNN F1- score, %	LSTM-TCN F1- score, %
5	75.42	78.12	80.76	88.56
10	77.55	81.12	83.75	91.29
15	79.75	83.45	86.01	92.98
20	81.01	84.73	87.42	94.25
30	82.43	86.30	88.89	95.72

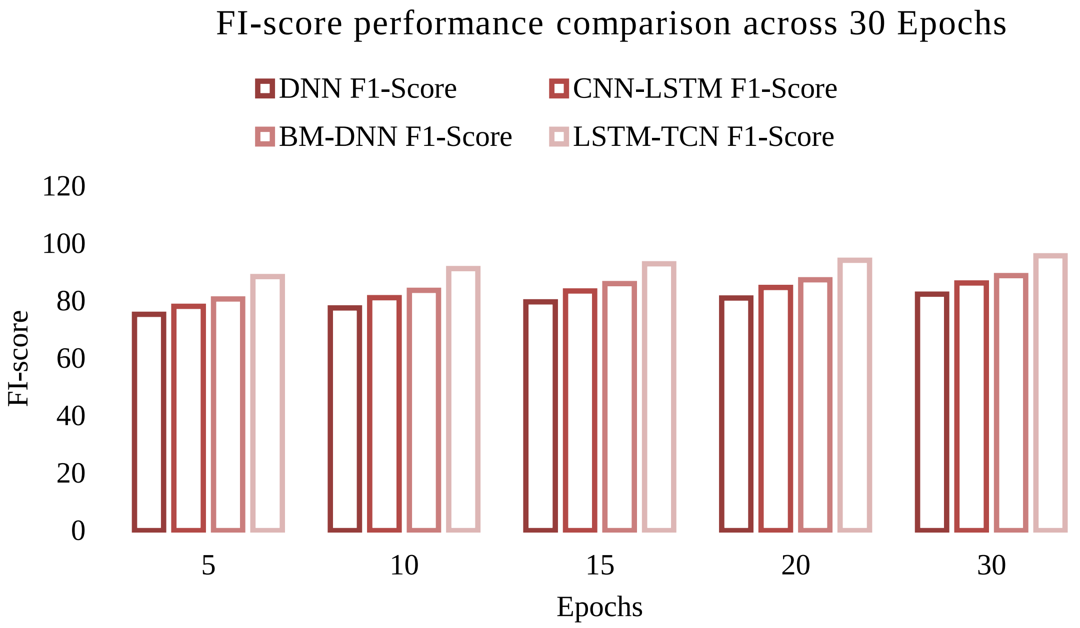

Figure 6. Performance analysis of F1-score

Conclusion

The suggested crop yield prediction model indicates a remarkable development on the use of data-driven intelligence to forecast agriculture through the adoption of strong preprocessing, time-conscious feature selection, and integration of hybrid deep learning. Min-Max Z-Scaling will enable the system to effectively address inconsistency and large scale variations in the heterogeneous environmental and soil variables to provide better model stability and convergent speed. Further improvement of prediction quality is the temporal Trend Signature Feature Selection (T-TSFS) algorithm that isolates those temporal trends and removes redundant or noisy attributes that are usually a setback to conventional ML and DL architecture. The hybrid LSTM-TCN model provides a better predictive ability because of the combined long-term climatic and temporary seasonal variation with the multi-scale temporal correlations, which characterize crop productivity. The achievement of the experiment in a variety of metrics of evaluation proves that the combination of the three stages makes more accurate, consistent, and generalizable predictions than current DNN, CNN-LSTM, and BM-DNN methods. The system is also highly resilient to the temporal irregularities, non-linear climatic variations, as well as data noise which are significant constraints in conventional models. Altogether, the suggested methodology has a great deal of reliability and scalability to be used in the real-world precision agriculture that will provide value to the decision-making process, resource optimization, and sustainable agriculture. Through this work, therefore, a solid computational basis on agricultural analytics in the next generation is provided and clears the way to combine the spatial data, remote sensing, and adaptive learning systems in future research.

Author Contributions

The successful completion of this research work was made possible through the valuable collaboration and collective efforts of all the authors. Dr. J. Jebamalar Tamilselvi played the primary role in developing the methodology and structuring the overall research framework. D. Sasikala, T. Murali, and Malini M provided significant support in dataset collection, technical inputs, and guidance during the manuscript preparation and writing process. The combined contributions of all authors enriched the study with diverse expertise and ensured the quality and completeness of the research work.

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Data Availability Statement

The corresponding author can provide the datasets upon request.

Conflicts of Interest

Hereby we are declaring that there is No Conflict of Interest related to this manuscript.

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