

# Minimax-Optimized Deep Learning Approach for Millet Yield Prediction Using an Improved LeNet-CNN

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## Abstract

Crop genotypes, conditions, and agricultural techniques influence the environmental crops that yield forecasts. The present investigation used large datasets from weather conditions, soil, and crop characteristics to examine how effectively machine learning and deep learning algorithms can forecast millet harvests. We propose the use of an "Ample LE\_ NET CNN(ALEN-CNN)" to utilize the convolution process to capture the time dependence of the environmental variables. ALEN-CNN is selected for its ability to model nonlinear relationships and capture spatiotemporal dynamics effectively, which are essential for accurate millet yield prediction under varying environmental conditions. In this instance, off-splitting normalization was performed to preprocess the information. Periodic features that might be retrieved using greedy trap fuzzy clustering and that specifically consider moisture levels in the soil and weather-related incidents were then used to address the seasonality ALEN-CNN was used. The proposed CNN performed better than the other machine learning models evaluated for predicting millet output in Tamil Nadu. Nonlinear models, such as deep learning models, have a stronger relationship between crop yield and input information than linear frameworks, and Deep Neural Networks outperform conventional methods in terms of prediction accuracy. The proposed ALEN-CNN model outperformed existing methods, achieving high accuracy (99.9%), F1 score (98%), and recall (94.6%) in millet yield prediction.

**Keywords:** Millet; Crop yield; off splitting normalization; greedy trap fuzzy clustering; Ample LE\_ NET CNN(ALEN-CNN)

## Introduction

Millet or Bajra is extensively farmed in Africa, Asia, China, and the Russian Federation and may be used as a grain or as an ingredient in many dishes. Either grain or grazing land, pearl millet is a highly prized grain. Vital and drought-resistant cereal crops are staple foods for human nutrition. In most cases, rainwater is used as a water source. A crop is grown on a small area of land with limited resources and minimal oversight. It is a food crop cultivated by many people living in tropical Africa and India. The Sahelian West is the primary manufacturing location. Brief durations of high-temperature droughts and sandy soil are common features of the planting season in these areas. Soils that are incapable of supporting life. The seeds of these grasses are tiny, and cereals are typically grown for this purpose. In India, where millet has been farmed for a long time, it is one of the most widely consumed crops in the country. Longitudinal growth has been observed over the years. Academic and governmental

scientists have conducted annual millet yield investigations since 1941. India is regarded as one of the most important countries in the world. The second-largest source of pearl millet is the wide variety of plants that grow across the nation. Pearl millet is an important food source. Most of it is cultivated in Rajasthan, Uttar Pradesh, Tamil Nadu, Gujarat, and Haryana, all in Madhya Pradesh. Trials were conducted to assess the adaptability of new and existing cultivars under various conditions. The data from these studies, both old and new, may be employed to increase forecasting accuracy by considering the genomic and ecological aspects.

Forecasting performance in fresh and unknown environments is a significant issue in plant breeding and agricultural production. In this fast-paced scientific field, it takes time and money to produce an extensive database of a broad variety of genotypes and environments. Because of the time and effort required to manage large numbers of plots, administration, and long-term ecological consequences, studies have mostly been conducted at modest scales. It has become increasingly necessary to attribute environmental variations to a general "environmental" component as each layer of further characterization of the environment is provided. Regardless of the crop species, plant breeding techniques are built on the intersection of genetic and non-genetic elements to solve future crop production difficulties. Climate adaptability is a top priority for plant breeders and farmers, as they desire varieties that produce high-quality seeds under a range of conditions. Climate change may be associated with variations in temperature, rainfall, and other atmospheric factors. Notwithstanding its significance in forecasting studies, spatial variation frequently takes precedence over temporal variations in atmospheric elements. It is crucial to recognize how such discrepancies impact agronomic output because human-caused worldwide changes in the environment have increased the frequency and intensity of extreme climatic occurrences. Forecasting the effects of changing environmental conditions on productivity may be useful for decisions on plant breeding and marketing, increasing output, and assessing results over an extended period of time.

In the past, models have been created to simulate and predict agricultural output under various climatic conditions, genotypes, soil types, and management characteristics of crops. Their input factor estimates and forecasts in unexpected settings are inadequate, although they offer a decent description of biophysical causes and reactions. Previously, yield representations were developed by analyzing reactions with a restricted number of lines, whereas modifying a solitary environment-related parameter was used to forecast yield across environments. Linear models have been successfully employed to overcome the limitations of crop growth models for yield prediction. Many of these low-capacity models have difficulty accounting for complex biological interactions and large regional climatic factors. It has been shown that conventional linear methods, such as Autoregressive Integrated Moving Average (ARIMA), are effective in forecasting upcoming phases in a similar timeframe. Random forest was employed to forecast grid cell yield differences because climatic extremes are important for agricultural projections. For time-series forecasting, Deep Neural Networks (DNNs) can approximate nonlinear functions and manage noisy inputs. Deep learning algorithms may provide solutions when confronted with various environmental factors, developmental stages, and genetic information. Such frameworks can efficiently study nonlinear relationships between multivariate input records and expected yields. Le-networks can identify long-term time-based correlations in challenging multivariate series, making them useful for time-series modeling. However, these models are incomprehensible. Field-scale data were replaced with geospatial data in the absence of regular weather statistics.

In recent decades, a wide variety of solutions have been proposed to address the "interpretability" problem. However, each of these methods has disadvantages. Thus, we created a model that can forecast millet production from an Indian database of field trials covering four years by capturing the temporal variability of multiple meteorological factors during the growing season. Crop yield can be predicted using a model based on CNN and clustering methods. The proposed technique was more accurate in predicting crop yields via MATLAB simulations. Our study yielded the following results.

1. Deep learning (DL) is used as an analytical tool for rapid decision-making and immediate evaluation of massive volumes of information.
2. It is used in combination with clustering and classification to address prediction issues.

The remainder of this paper includes the views of deep learning systems on crop yield prediction, and recent approaches are analyzed in Sections 1 and 2. The problems associated with crop yield prediction are described in Section 3. Section 4 describes the proposed model. Section 5 outlines the simulation results, and Section 6 concludes the study.

## Related Works

Based on previous research, we further explored the application of deep learning in millet yield prediction, as detailed in the following review of related work.

### **Deep Neural Networks (DNNs)**

Khaki and Wang [1] developed a DNN methodology to take advantage of innovative modeling and solution methodologies. The validation dataset, which included anticipated meteorological data, showed that their model had a “root mean square error (RMSE)” of 12% for the mean production and 50% for the standard deviation (SD). To minimize the RMSE by 11% of the mean production, a 46% SD would require accurate weather information. Using the trained DNN model, they were able to reduce the size of the input area, thereby lacking a substantial decrease in the forecast precision.

Wang et al. [2] predicted soybean crop yields in Argentina with a high accuracy. With less data, they also predicted the Brazil soybean output by applying a transfer-learning approach. A large amount of training data is required for deep learning models to be successful. Therefore, transfer learning is crucial in this context. The ability to fine-tune previously learned models is essential for successful agricultural production prediction using deep learning in areas with limited training data.

### **Convolutional Neural Networks (CNNs)**

Neuvauoriet al. [3] developed Crop yield prediction models using UAV-derived NDVI and RGB data using the “Convolutional Neural Networks (CNNs)”, an innovative training tool with impressive behavior in image categorization challenges. The accuracy of the CNN predictions was examined as a function of a range of CNN parameters, including the method used for training, network depth, regularization, and hyper parameter tuning. To accurately forecast agricultural production.

An example of a revolutionary 3D CNN suited to these inherent data restrictions was presented by Fernandez et al. [4]. Third, they examined how different data configurations affect the performance of the proposed method and other innovative regression- and CNN-based yield estimation techniques.

### **Artificial Neural Networks (ANNs) and Hybrid Models**

Gopal et al. [5] used a hybrid MLR-ANN model. As an initialization step for the input layer weight and bias of the ANN, the authors used the MLR intercept and coefficients to establish a hybrid model. To accurately anticipate the yield of a paddy crop, “Feed Forward ANN with back propagation” training was utilized. In a standard ANN model, the input and hidden layer weights and biases are initially randomly generated. The initial layer weights and biases in this hybrid MLR-ANN algorithm were initialized using the MLR coefficients and bias. Using deep learning algorithms.

Elavarasan and Vincent [6] used the Q-Learning reinforcement learning method in conjunction with a Recurrent NN (RNN) DL Algorithm to build a model for predicting crop productivity. Recurrent Neural networks are supplied with data parameters and have several layers. This network creates a crop production forecasting scenario using the supplied parameters. The output values of the RNN were converted into Q-values using a linear layer. Using a mix of parametric parameters and thresholds, the reinforcement learning agent can estimate the crop productivity.

For Indian rice-producing regions, a review of the use of this machine learning technology was presented by Gandhi et al. [7]. The “WEKA tool” was employed to classify details from 27 districts in Maharashtra State, India, and the findings of the experiment are presented in this publication. Researchers in the Indian state of Maharashtra employed NNs to calculate rice yield and analyze the parameters that influence rice crop production (Gandhi et al. [8]). Records from the Indian government were used to compile the data, which included 27 districts in Maharashtra.

### **Support Vector Machines (SVMs)**

Technological advancements have increased the use of machinery and control systems to automate procedures and boost output. To forecast agricultural productivity per acre, this study used multivariate polynomial regression, SVM regression, and RF frameworks. The output and meteorological information from the “United States Department of Agriculture” were used in the proposed technique. The SVM regression method suggested by Brdar et al. [9] outperforms earlier findings produced using model trees, according to their research. As a black-box model, SVM regression does not provide a reason for the prediction.

Rajak et al. [10] fed soil testing lab data into the recommendation system, which creates an ensemble model utilizing the majority voting approach, SVM, and ANN as learners to accurately and efficiently select a crop for a site-specific parameter.

### **Machine Learning and Big Data**

Palanivel et al. employed various Machine Learning (ML) algorithms to estimate agronomic yields. [11]. ML methods have been employed to estimate agronomic yields using the Big Data computing paradigm. Sahu et al. [12] presents a reason for utilizing a big data method to identify experiences based on accurate agricultural facts. Consequently, a framework for substantial computational issues in crop analysis when information is acquired remotely is driven by the need for efficient data collection. The Hadoop architecture was used to store a large amount of agricultural data to meet the storage needs of agriculture. Their research helps farmers better forecast which crops to grow in their agricultural fields, depending on the composition of their soil, thereby increasing production.

### **Other Techniques**

The yield was predicted, and the best climate conditions were recommended by Shah et al. [13] to optimize crop production. Son et al. [14] created a technique employing the “MODIS Enhanced Vegetation Index (EVI) and Leaf Area Index (LAI)” for forecasting rice output in the Vietnamese Mekong Delta. Four fundamental categories were used to group the data processing steps: the first four parts of this study included the construction of vegetation indicators over time, noise filtration of time-series information employing Empirical Mode Decomposition (EMD), crop production framework generation, and framework justification. According to the study findings, EVI and LAI were the best variables to include in a quadratic model.

According to Jiang et al. [15], maize production can be predicted using an RNN with long short-term memory (LSTM). The sample space is sufficiently large for deep learning systems because of the data on county-level maize production and hourly weather parameters. The capacity of LSTM to predict time series with intricate internal links makes it a good match for this application. The explanatory variables and features were identified using Redundancy Analysis (RDA) by Dang et al. [16]. The interpretation rates of the explanatory components were evaluated using the basic effects of RDA. The characteristics of the explanatory factors were selected using the conditional effects of RDA.

These studies on crop yield prediction using deep learning and machine learning have shown promising results but also highlight key challenges. Models like DNNs and CNNs require large, high-quality datasets and are sensitive to parameter tuning. ANNs and hybrid models improve accuracy but can be complex to train and prone to variability. SVMs offer good performance but lack interpretability. Big data approaches face difficulties in handling noisy, unstructured data and require substantial computational resources. Overall, data quality, model complexity, and regional generalization remain common challenges across these methods.

### **Problem Statement**

Accurately forecasting agricultural yields remains a significant challenge due to the complex and variable interactions between environmental factors such as weather and soil conditions. These variables influence crop growth and productivity in unpredictable ways, making yield estimation difficult across seasons and regions. While agronomic practices like planting schedules, fertilization, and irrigation can mitigate some weather-related impacts, the lack of scalable, reliable forecasting methods limits their effectiveness. Traditional long-term field studies, which are essential for understanding sustainable land and crop management, are resource-intensive and impractical over large geographical areas. This highlights a critical research gap and the urgent need for robust, data-driven approaches. In this context, deep learning models such as Convolutional Neural Networks (CNNs) offer a promising solution, as they can efficiently capture nonlinear patterns and spatiotemporal dependencies, enabling accurate and scalable crop yield predictions under diverse environmental conditions.

### **Proposed Work**

The input and output regions should be properly connected according to an algorithm designed for deep learning. Thirty-three districts in Tamil Nadu were the subjects of the present research. Tamil Nadu is an ideal case study for millet yield prediction due to its diverse agro-climatic conditions, long history of millet cultivation, and vulnerability to climate variability. As one of India's top millet-producing states, it offers a wide range of environmental and soil conditions that challenge yield stability, making it suitable for testing advanced predictive models. The presence of rich historical data, government-supported millet programs, and reliance on rainfed agriculture by smallholder farmers further enhances its relevance. Studying Tamil Nadu allows the development of accurate, scalable deep learning models with potential application in similar semi-arid regions. Figure 1 shows the region of concern, districts under investigation, their corresponding legends, topographical characteristics, and geographic

boundaries. With nearly one-third of the state's GDP coming from agriculture and employing around three-quarters of the workforce, it is the state's largest economic sector. The most significant basic crop in the nation is millet, which contributes 20.75 percent of the overall GDP. Most of Thailand's millet is produced in the Tamil Nadu states, which is the largest millet-producing area in the country. Consequently, the long-term sustainability of the region's grain production system has a significant impact on Tamil Nadu's domestic food security. Tamil Nadu must spend more on agricultural research and development since the agricultural industry is not growing fast enough to meet the requirements of the expanding population for food. These and other variables have made it challenging to produce food efficiently and sustainably, particularly in regions with higher degrees of geographic and temporal differences.



Figure 1 Study region

### Data Collection

All datasets used in this analysis for 2017–2020 were obtained from documents made available to the public by the Indian Government. The following variables were considered in this study.

**Rainfall (mm):** Most freshwater on the globe is conserved by rainfall, which is an essential component of the water cycle. The total yearly precipitation during the Kharif season (June–November) was estimated using the average monthly precipitation for each district from 2017–2020.

**Temperature(°C):** The temperature (°C) significantly affects the rate of plant development. Temperature changes, environmental changes, and extreme temperatures affect agricultural productivity. The mean, minimum, and maximum temperatures for each district from (2017 to 2020) were included in this study. The mean, minimum, and maximum temperatures during the Kharif season (June–November) were estimated using the monthly average temperatures.

**Evapotranspiration**, which is used to calculate the amount of water lost through evaporation and plant transpiration, includes water vaporization and plant transpiration from the Earth's terrestrial and marine sides. A reference crop was constructed based on the monthly mean evapotranspiration from previous years for each region.

**Season:** From 2017 to 2020, throughout the Kharif season, we focused on the Tamil Nadu millet-growing area for the purpose of conducting this study (June–November). This study considered millet production in the study area during the Kharif season (June–November).

The quantity of millet yielded, and the region farmed in the Kharif season from 2017 to 2020 were used to calculate the yield (tons/hectare) for each district in Tamil Nadu that was selected for this research.

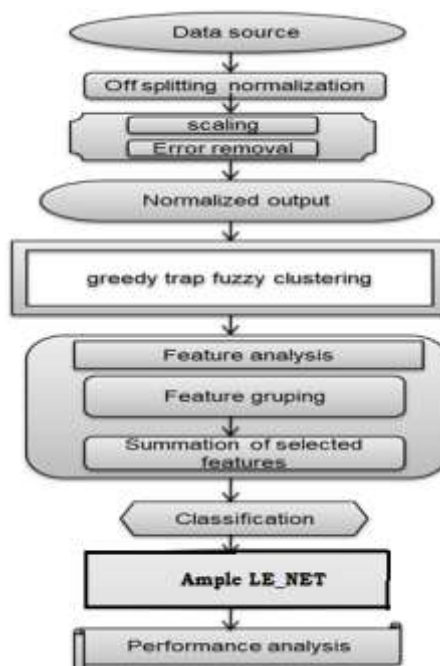


Figure 2 Schematic representation of the suggested methodology

### Normalization

Normalization is one of the most important components of this task. The term "normalization" refers to any technique that converts a collection of data values into a more usable form. Performing an appropriate analysis becomes difficult when there is substantial variance among the possible values of the provided parameters for a dataset. Any technique aiming to learn from information will find it difficult to do so if the results of numerous factors or variables vary significantly. However, the normalized data support the implementation of faultless and precise machine learning. The technique for normalizing data that is most often used in this study is off-splitting normalization. In the preprocessing step, which attempts to remove any unwanted systematic variation in the data, we propose a method that leverages variability to identify an optimal normalizing factor. The data variation can be calculated by calculating the observed variance in the data intensity.

$$Y_{ab} = \sum_{a=0}^{\infty} (-1)^a \binom{n}{a} m_a \times xy_{ab}(N) \times e_{ab}, \quad (1)$$

Here  $y, x_{ab}$  represents the data difference  $m, n, e$  indicates the error constant  $a, b$  represents the hat function,  $N$  indicates the normalization parameter. Here,

$$N = \log x, \Omega = \log N, \mu = \log m, (\Omega) = \log r(N), \varepsilon = \log e$$

$$y_{ab} = \mu_a + p_{ab}(\Omega) + \varepsilon_{ab}.$$

The uncertainty of the input error,

$$p_{ab} = \sum_s \mu_{as} (\Omega_{sb} - \langle \Omega_s \rangle) \quad (2)$$

Here the average  $\langle p_{ab} \rangle$  is taken over the sample  $b=1 \dots M$ , i.e.

$$\langle \Omega_s \rangle \equiv \frac{1}{M} \sum_b \Omega_{sb}.$$

The internal standard's variability is committed more strongly to the standardizing correction coefficient for error peak  $a$  by the variables  $\mu$ , which link the variation of intensities with the variation of internal standard intensities.

$$q(t) = \prod_z \left( \ell(hg, hg)^{x_z} \ell(Hb(uad), hg) \frac{v_z}{usk} \right) = 0 \quad (3)$$

Where  $v = R - 2$

Using this method, an error-free hat equation was derived.

$$p_c = \bar{q}_c \quad (4)$$

$$Q_c = \frac{\bar{q}_w - \mu_w / E}{\sigma_E} \quad (5)$$

$$y_c = \frac{\bar{q}_w - \mu_E / b}{\sigma_b} \quad (6)$$

The probability variance for the function's normalization may be represented as,

$$Mp_c = \frac{\hat{t}_c - \mu_E/h}{\sigma_b} \quad (7)$$

$$MQ_c = \hat{t}_{E_b} \quad (8)$$

$$MY_c = \frac{\hat{t}_{E_c} - \mu_c/E}{\sigma_E} \quad (9)$$

Consider that the Hat matrix shall be consider N,

$$\begin{aligned} n = \overrightarrow{N_1} &= \frac{(0.4 * Fm(b) - Fm_{min})}{Fm_{max} - Fm_{min}} \\ \overrightarrow{N_2} &= \frac{(0.6 * Fm(b) - Fm_{min})}{Fm - Fm_{min}} \end{aligned} \quad (10)$$

(11)

The hat matrix shall be estimated by utilizing the equation,

$$\begin{aligned} \tilde{n}_{ab} &= (0.4 * 0.6) \beta X_{ab} \times \exp - \sum_{s=1}^s \hat{\beta}_{as} (\Omega_{sb} - \langle \Omega_s \rangle) \\ &* \left( \frac{(\prod_{k=1}^M N_{1K})^{\frac{1}{M}}}{N_{1b}} \right)^{\frac{r_{a1}}{\sigma_a^2}} \end{aligned} \quad (12)$$

The upgraded normalized function may be expressed by,

$$r_{a1} = \tilde{N}_{ab} \sum_{b=1}^M (\log X_{ab} - \langle \log X_a \rangle) (\log Z_{1b} - \langle \log z_{1.} \rangle) \quad (13)$$

Where,

$$\sigma_a^2 = \vec{A} \cdot e^{gh} \cdot \cos(2\pi h) + \vec{P}^*(b)$$

### Feature clustering

As the name implies, greedy trap fuzzy clustering (GTFC) is centered on the impression that groups of connected characteristics shall develop, with similarities between groups being important and variances among groups being uncertain. The input data array is a feature characteristic data matrix. Elements with many features are the ones we want to group together because they have many things in common. The GTFC focuses mostly on its local surroundings, apart from its low degree of technical inspection. The GTFC has certain disadvantages, such as a focus on one location and a lower level of technical examinations. All information is represented by the equation below, which was created using the GTFC method.

$$\begin{aligned} v_0 &= GTFC \cdot \ell(hg, hg)^{sb}, \\ \sigma_r^2 &= v_1 = (hg, hg)^{x=}. (hg, hg)^{\lambda \zeta(n)rl=}, \\ Bv_2 &= hg^{rl=}, v_{3,n} = hg^{v=}. hg^{\varphi \zeta(n)rl=}, \forall n \end{aligned} \quad (14)$$

Here  $\sigma$  denotes the present iteration and  $v_0$  represents the regulatory component.

According to Eq. (15), increasing the number of repetitions leads to smaller data structures. The introduced methodology was used to estimate the Euclidean distance between the characteristics. Based on this, the grouping was performed.

$$Y_{ED} = b + \sum_{a=1}^p f_a y_{r-a} + \epsilon_{r * \sigma_r^2} \quad (15)$$

Here  $Y_{ED}$  = fitness feature distance

It is crucial to determine the closest match centroid with comparable attribute matrices after determining the fitness distance.

$$D = \begin{bmatrix} 1 & 2 & 4 \\ 1/2 & 1 & 3 \\ 1/4 & 1/3 & 1 \\ 1/5 & 1/4 & 1/3 \\ 1/6 & 1/5 & 1/2 \end{bmatrix}$$

By utilizing the characteristics of matrices D, it is feasible to group information into one group, as shown in Eq. (16).

$$D = \{V1 + V2 + V3\} \quad (16)$$

Eq. (2) demonstrates that V1, a subset of E, comprises a group of items from the genotyping set.

$$V1 = \{r: r \in D\} \quad (17)$$

Eq. (18) and Eq. (19) demonstrate that V2 and V3 are also subgroups of D, with V2 and V3 consisting of a collection of meteorological and soil characteristics pertaining to the millet production,

$$V2 = \{s: s \in D\} \quad (18)$$

$$V3 = \{t: t \in D\} \quad (19)$$

The cropping properties can be carefully examined using the provided methods.

### Classification

ALEN-CNNs learn input data using convolutional layers. Kernels, the system's low-level components, are removed by this layer. During rotation, the convolutional operator is not invariant to the rotation. Data aggregation layers are another type of rising tier that is currently being developed. The CNN architecture consists of several interconnected components. The training process for the CNN was divided into two stages: feed and back-propagation. This step of the procedure involves contrasting the network results generated by a particular piece of information with the true labeled response of the system to determine the feed-forward errors. In the context propagation phase, which considers network errors, the computed gradient is applied to each weight matrix. The precision of CNNs in categorizing and their ability to conduct pertinent research on enormous datasets both improve with complexity. Ecological circumstances were evaluated by calculating the likelihood of success. The input function is mathematically expressed as:

$$(C, d) = \sqrt{(c_1 - d)^2 + (c_2 - d)^2 + \dots + (c_n - d_n)^2} \quad (20)$$

The formula is rewritten as,

$$v^{l+1}(c, d) = [Y^l \otimes w^{l+1}](c, d) + b = \sum_{k_l} \sum_f \sum_{f=1}^{e=1} \sum_{y=1}^{y=1} [Y_l(s_o c + x, s_o d + y) w_{l+1}^k(e, f)] + f$$

(21)

Where the distance amongst two multi-dimensional data points  $C = (c_1, c_2, c_3, \dots, c_n)$  and  $D = (d_1, d_2, \dots, d_n)$

The forecast function is assigned by,

$$Y^{l+1}(c, d) = \tau_{ij} = 1 + \tau_{ij} + \frac{p(i, j)}{\text{NumberOf features}}$$

$$(c, d) \in \{0, 1, \dots, y_{l+1}\}, y_{l+1} = \frac{y_l + 2q - f}{s_o} + 1 \quad (22)$$

Here

$$Y^1 = \sum_{k_l} \sum_f \sum_{f=1}^{v1=1} \sum_{f=1}^{v2=1} \sum_{f=1}^{v3=1} (Y_{c,d,k}^l w_{l+1}) = w_T^{l+1} Y_{l+1} + \frac{y_l + 2q - f}{s_o} + 1$$

The categorization is performed corresponding to the feature responsibility,

$$W_{kb} \frac{y^*}{\partial u_k} = \sum_{k=1}^k \sum_{i=1}^p (a_i - y_k)^2 \quad (23)$$

$$= \sum_{k=1}^k \sum_{i=1}^p \frac{\partial}{\partial y} (a_i - y_k)^2$$

$$= \sum_{i=1}^p 2(a_i - y)$$

Finally, millet production was forecasted based on the categorization.

### Performance Analysis

Millet serves a vital function in the rain-fed regions of the country, accounting for 60 percent of the total cultivated area. Minor millets are highly nutritious, rich in essential minerals, and well adapted to withstand drought and other environmental stresses common in rain-fed agriculture. Millet production was estimated after adopting the recommended classification according to the environment, genotype, and meteorological characteristics. The classification pattern of millet was examined, and the results are shown in Figure 3.

```

user input = Crop prediction dataset
year = 2021
crop_type = 'maize'
Area = "Virudhunagar"
Millet type= Common millet
Production= 16.955L.mt.
Rank='1'

```

**Figure 3 Classification output**

As shown in Figure 3, depending on the extracted features, Salem was considered a high-production unit, which acquired the first rank and had a high yield every year, with an average of 16.955L.mt.

**Table 1 Production and ranking output**

| State        | Area ('000 ha) | Yield (L.mt.) | rate (%) | Rank |
|--------------|----------------|---------------|----------|------|
|              |                |               | Yield    |      |
| Virudhunagar | 42.80          | 16.955        | 3.29     | 1    |
| Madurai      | 15.6           | 5.15          | 0.41     | 8    |
| Trichy       | 709.8          | 12.84         | 1.85     | 4    |
| Salem        | 58.8           | 8.35          | 0.77     | 7    |
| Theni        | 85.96          | 4.4           | 2.46     | 3    |
| Villupuram   | 124.37         | 13.56         | 3.5      | 2    |
| Coimbatore   | 10.4           | 11.69         | 1.41     | 6    |
| Krishnagiri  | 1210.94        | 15.34         | 1.78     | 5    |

The overall production rate of millet was classified as a major millet production area in Tamil Nadu, and its production ranking level is demonstrated in Table1.

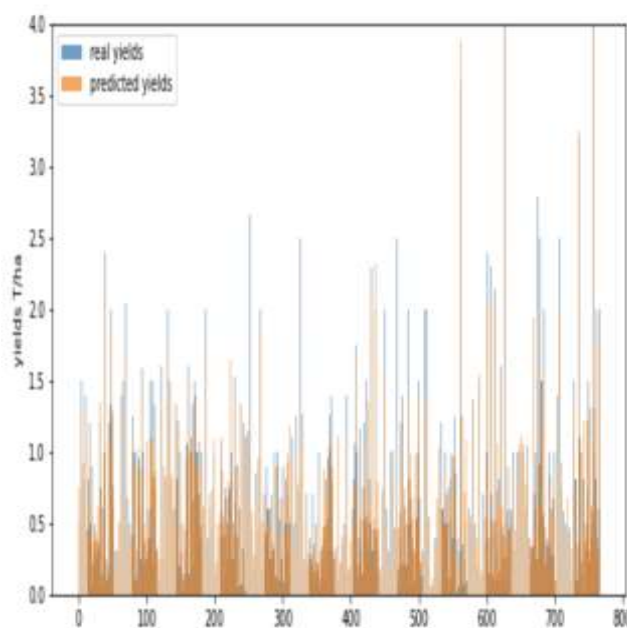


**Figure 4 Dataset Vs. yield prediction**

As shown in Figure 4, the suggested methodology has a slight variation over the millet yield prediction ground-truth results. Several execution or assessment metrics were used to evaluate the plausibility of

the model. Comparing this model with existing systems may help validate it [5]. The evaluation metrics used in this study are as follows.

The accuracy of the predictions was measured using the “Mean Absolute Percentage Error (MAPE).” They have the following names:

$$MAE = 1/NT * \quad (24)$$

Where  $NT$  is the number of the testing data, is the average energy spent, and is the average current availability projected value.

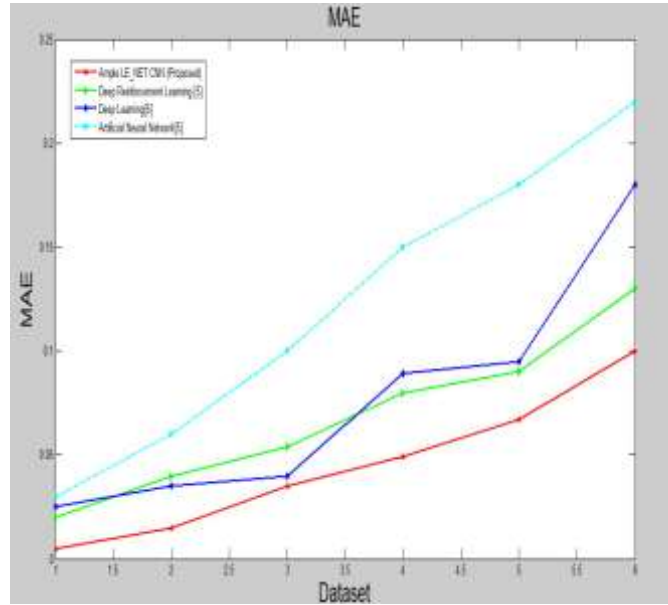


Figure 5 Dataset Vs. MAE

According to Figure 5 and Table 3, the MAE of the proposed methodology was significantly lower than that of the conventional algorithms.

MSE is represented by:

$$MSE = \sum_{i=0}^{a-1} \sum_{j=0}^{b-1} \sum_{s=0}^2 ||g(i, j, s) - f(i, j, s)||^2 \quad (25)$$

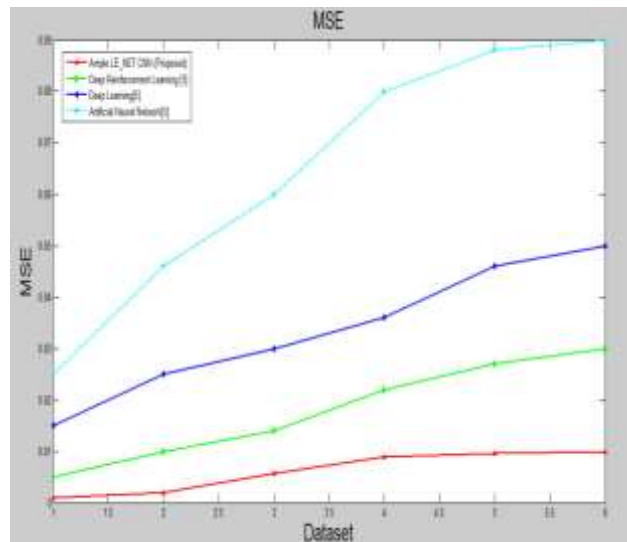


Figure 6 Dataset Vs. MSE

The MSE in Figure 6 and Table 4 is low. Consequently, the proposed technique has a lower error rate than that of millet crop prediction.

Using RMSE, the whole crop forecast error rate may be represented by,

RMSE is expressed by:

$$RMSE = \sum_{i=0}^{a-1} \sum_{j=0}^{b-1} \sum_{s=0}^2 ||g(i, j, s) - f(i, j, s)||^2 \quad (26)$$

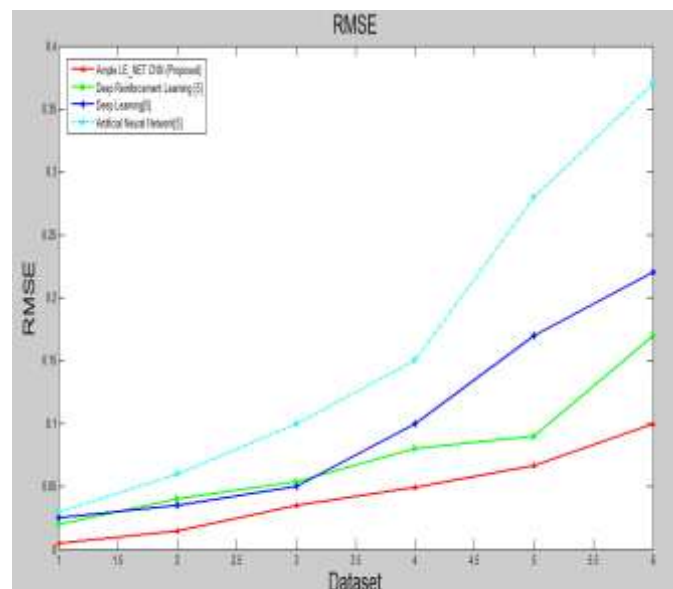


**Figure 7 Dataset Vs. RMSE**

As shown in Figure 7 and Table 5, the recommended technique is effective, as indicated by the low RMSE value for crop forecasting. Compared with other current techniques, the average error rate of the proposed model for millet crop prediction was low at 0.08%.

The forecasting accuracy was measured using the mean absolute percentage deviation (MAPD). Accuracy is often expressed as a ratio, specified by the following mathematical expression:

$$\text{MAPE} = \frac{-At \pm 100\% \sqrt{Ft^2 - 4}}{A} \quad (27)$$

Here  $At$  denotes the actual value and  $Ft$  denotes the predicted value. Their variance is divided by  $At$ . The true values corresponding to each forecasted time point are added together, and the total is then divided by the number of fitted points, denoted as  $n$ .

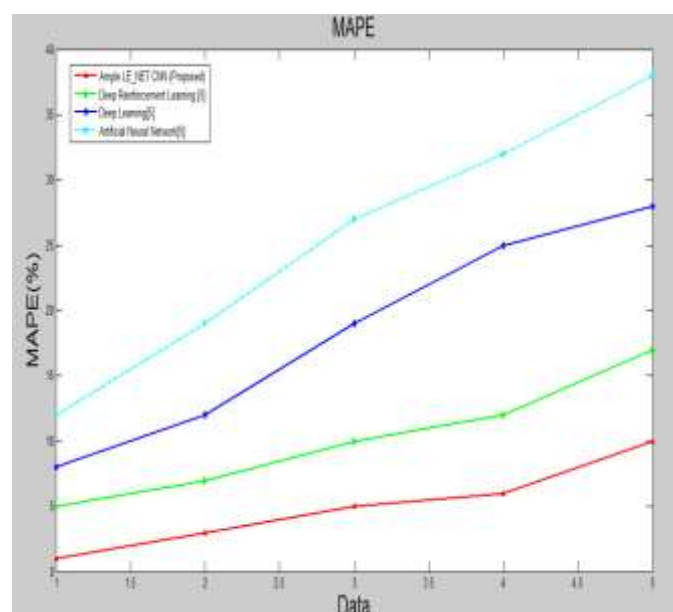


**Figure 8 Data Vs. MAPE**

The mean absolute error of the proposed mechanism was 6% as shown in Figure 8 and Table 6, which is lower than that of conventional methods. Metrics, including Accuracy, Precision, F1-score, and Recall, were used to assess the effectiveness of the novel approaches. Four important variables should be considered when performing this evaluation, and it is crucial to understand the distinctions between true negative (TN), true positive (TP), false positive (FP), and false negative (FN) results. The data items that the algorithm correctly identified were considered true positives. The data numbers that the system correctly classified as negative TNs were named. FP is characterized by characteristics that are

seen as favorable but not always the same. It is used to describe negative integers with unknown precise values.

- TP indicates that a crop may be able to grow in a certain area.
- TN indicates that the probability is unknown.
- FP stands for crop growing potential detected but not present.
- FN denotes that there is a possibility, but this has not been determined.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (28)$$

$$Precision = \frac{TP}{TP+FP} \quad (29)$$

$$Recall = \frac{TP}{TP+FN} \quad (30)$$

$$F_1 = \frac{2*Precision*Recall}{Precision+Recall} \quad (31)$$

$$TPR = \frac{TP}{TP+FN} \quad (32)$$

$$FPR = \frac{FP}{FP+TN} \quad (33)$$

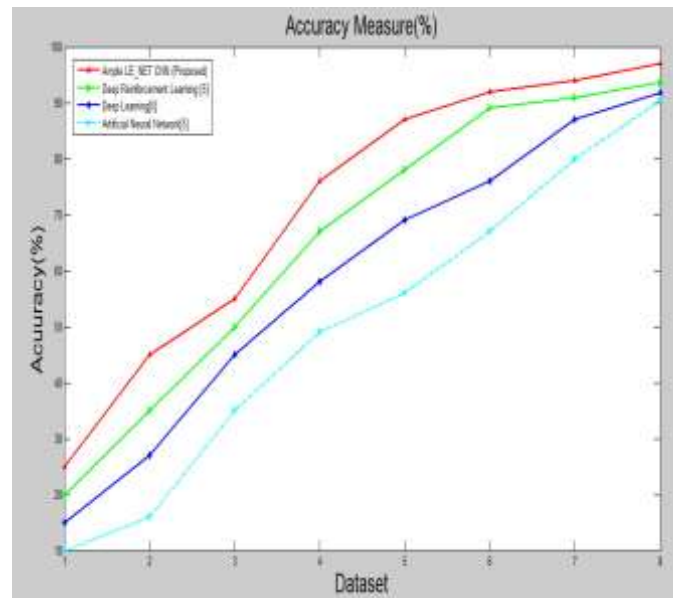


**Figure 9 Dataset Vs. Accuracy**

Figure 9 and Table 7 shows the proposed categorization approach, which outperformed the other current mechanisms with a maximum accuracy of 97.8%.

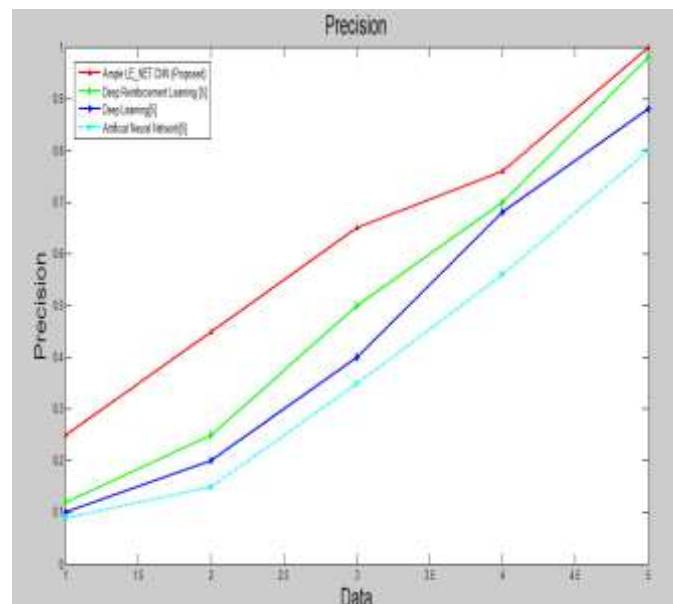


**Figure 10 Data Vs. Precision**

The constructed model, as shown in Figure 10 and Table 8, has a much higher accuracy rate (99.9%) than that currently in use.

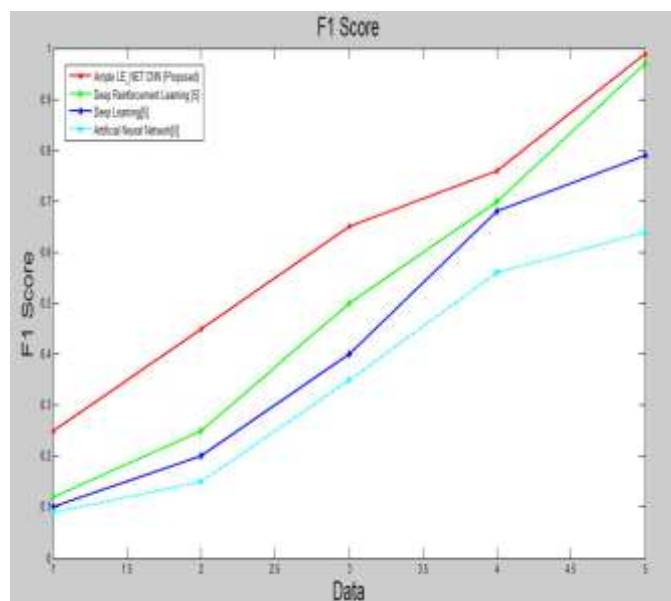


**Figure 11 Dataset Vs. F1 score**

Figure 11 and Table 9 show the F1 grade for the solution. The results showed that the coefficient of the F1 score was 98% according to the recommended method.

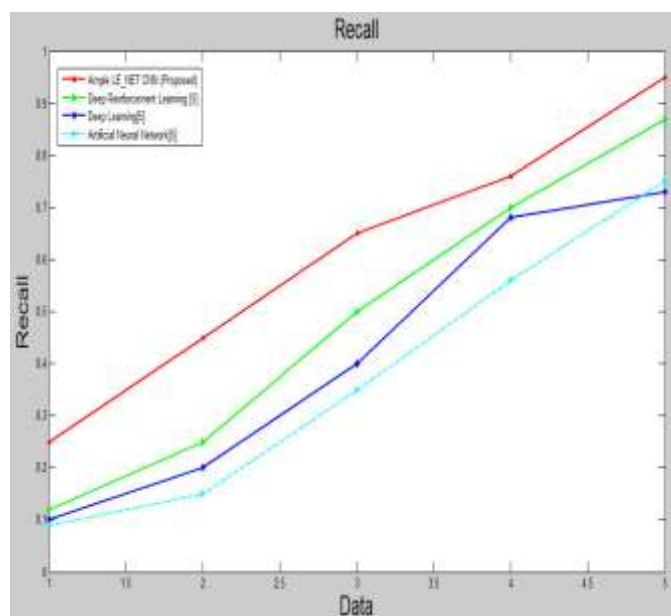


**Figure 12 Dataset Vs. Recall**

Figure 12 and Table 10 display a greater recall of 94.6%, which is better than that of traditional algorithms. Table 2 shows the algorithm performance.

Hence, in contrast to various contemporary methods, the findings show that the recommended ALLEN-CNN model expresses satisfactory outcomes for millet production forecasting.

## Conclusion

Artificial Intelligence algorithms have become more self-reliant and intelligent owing to the development of Deep Learning-based classification, which has spurred the development of new agricultural production forecast systems. The accuracy and efficiency of the proposed ALLEN-CNN for millet yield prediction were demonstrated by the results of precision and efficiency tests. By building a production forecast environment via self-discovery and experience rewind, the advised technique

allows learners to discover and gain knowledge of crop production forecasts. The dataset forecast results showed that the technique was controlled by the production forecasting agent, demonstrating the effectiveness of the proposed methodology in identifying the behaviors of millet crop production. Integrating greedy trap fuzzy feature extraction and ALEN-CNN-based autonomous empirical evaluation is key to obtaining the desired results. The suggested methodology offers a comprehensive answer that mines the nonlinear mapping among crop production and meteorological, soil, and genetic characteristics, unlike supervised learning-based crop yield forecasting procedures. When constructing millet crop production prediction models, this benefit may reduce the need for experts and past data to some extent. Thus, a more generic model for yield prediction was developed using the suggested technique. The proposed framework for millet crop yield prediction achieved 98 percent accuracy over crop prediction and will help form a more robust operational model in the future. An exciting possibility is to further increase the computational efficacy of the training process.

While the proposed ALEN-CNN model demonstrates high accuracy in predicting millet yields, certain limitations remain. The model's performance is highly dependent on the quality, completeness, and granularity of the input data, including weather, soil, and crop-specific parameters. Additionally, the model may have limited generalizability when applied to regions or crops not represented in the training dataset. Future work will focus on extending the approach to other cereal crops and diverse agro-climatic zones to enhance its robustness. Real-time deployment and integration with remote sensing data and decision support systems will also be explored to support dynamic agricultural planning and on-ground decision-making.

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## CONFLICT OF INTEREST - MANDATORY

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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